

Firm-Level Political Risk: Measurement and Effects*

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Abstract

We adapt simple tools from computational linguistics to construct a new measure of political risk faced by individual US firms: the share of their quarterly earnings conference calls that they devote to political risks. We validate our measure by showing it correctly identifies calls containing extensive conversations on risks that are political in nature, that it varies intuitively over time and across sectors, and that it correlates with the firm's actions and stock market volatility in a manner that is highly indicative of political risk. Firms exposed to political risk retrench hiring and investment and actively lobby and donate to politicians. These results continue to hold after controlling for news about the mean (as opposed to the variance) of political shocks. Interestingly, the vast majority of the variation in our measure is at the firm level rather than at the aggregate or sector level, in the sense that it is neither captured by time fixed effects and the interaction of sector and time fixed effects, nor by heterogeneous exposure of individual firms to aggregate political risk. The dispersion of this firm-level political risk increases significantly at times with high aggregate political risk. Decomposing our measure of political risk by topic, we find that firms that devote more time to discussing risks associated with a given political topic tend to increase lobbying on that topic, but not on other topics, in the following quarter.

JEL classification: D8, E22, E24, E32, E6, G18, G32, G38, H32

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From the UK’s vote to leave the European Union to the threats of the US Congress to shut down the federal government, recent events have renewed concerns about risks emanating from the political system and their effects on investment, employment, and other aspects of firm behavior. The size of such effects, and the question of which aspects of political decision-making might be most disruptive to business, are the subject of intense debates among economists, business leaders, and politicians. Quantifying the effects of political risk has often proven difficult due to a lack of firm-level data on exposure to political risks and on the kind of political issues firms may be most concerned about.

In this paper, we use textual analysis of quarterly earnings conference-call transcripts to construct firm-level measures of the extent and type of political risk faced by firms listed in the United States—and how it varies over time. The vast majority of US listed firms hold regular conference calls with their analysts and other interested parties, in which management gives its view on the firm’s past and future performance and responds to questions from call participants. We quantify the political risk faced by a given firm at a given point in time based on the share of conversations on conference calls that centers on risks associated with politics in general, and with specific political topics.

To this end, we adapt a simple pattern-based sequence-classification method developed in computational linguistics (Song and Wu, 2008; Manning et al., 2008) to distinguish between language associated with political versus non-political topics. For our baseline measure of overall exposure to political risk, we use a training library of political text (i.e., an undergraduate textbook on American politics and articles from the political section of US newspapers) and a training library of non-political text (i.e., an accounting textbook, articles from non-political sections of US newspapers, and transcripts of speeches on non-political issues) to identify two-word combinations (“bigrams”) that are frequently used in political texts. We then count the number of instances in which these bigrams are used in a conference call in conjunction with synonyms for “risk” or “uncertainty,” and divide by the total length of the call to obtain a measure of the share of the conversation that is concerned with political risks.

For our topic-specific measure of political risk, we similarly use training libraries of text on eight political topics (e.g., “economic policy & budget” and “health care”), as well as the political and non-political training libraries mentioned above, to identify patterns of language frequently used when discussing a particular political topic. This approach yields a measure of the share of the conversation between conference call participants that is about risks associated with each of the eight political topics.

Having constructed our measures, we present a body of evidence bolstering our interpretation that they indeed capture political risk. First, we show that top-scoring transcripts correctly identify conversations that center on risks associated with politics, including, for example, concerns about regulation, ballot initiatives, and government funding. Similarly, the bigrams identified as most indicative of polit-

ical text appear very intuitive—e.g., “the constitution,” “public opinion,” and “the FAA.”

Second, we find our measure varies intuitively over time and across sectors. For example, the mean across firms of our overall measure of political risk increases significantly around federal elections and is highly correlated with the index of aggregate economic policy uncertainty proposed by [Baker et al. \(2016\)](#), as well as with a range of sector-level proxies of government dependence used in the literature.

Third, we show that our measure correlates with firm-level outcomes in a way that is highly indicative of reactions to political risk. Specifically, conventional models predict that an increase in any kind of risk, and therefore also an increase in the firm’s political risk, should trigger a rise in the firm’s stock return volatility and decrease its investment and employment growth (e.g., [Pindyck \(1988\)](#); [Bloom et al. \(2007\)](#)). In contrast to such “passive” reactions, firms may also “actively” manage political risk by donating to political campaigns or lobbying politicians ([Tullock, 1967](#); [Peltzman, 1976](#)). Such “active” management of political risks, however, should be concentrated among large but not small firms, as large firms internalize more of the gain from swaying political decisions than small firms ([Olson, 1965](#)).

Consistent with these theoretical predictions, we find that increases in our firm-level measure of political risk are associated with significant increases in firm-specific stock return volatility and with significant decreases in firms’ investment, planned capital expenditures, and hiring. In addition, we find that firms facing higher political risk tend to subsequently donate more to political campaigns, forge links to politicians, and invest in lobbying activities. Again, consistent with theoretical predictions, such active engagement in the political process is primarily concentrated among larger firms.

Having established that our measure is correlated with firm-level outcomes in a manner that is highly indicative of political risk, we next conduct a series of falsification exercises by modifying our algorithm to construct measures of concepts that are closely related, but logically distinct from political risk, simply by changing the set of words on which we condition.

A key challenge to any text-based measure of risk is that news about the variance of shocks may be correlated with (unmeasured) news about their conditional mean – and such variation in the conditional mean may confound our estimates of the relation between political risk and firm actions. To address this challenge, we modify our methodology to measure the sentiment expressed by call participants when discussing politics-related issues. Specifically, we modify our algorithm to count the same political bigrams as used before, but now condition on their use in conjunction with positive and negative tone words, rather than synonyms for risk or uncertainty. We find that this measure of political sentiment has all expected properties. For example, it correctly identifies transcripts with positive and negative news about politics, and more positive political sentiment is associated with higher stock returns, investment, and hiring. Nevertheless, controlling for political sentiment (and other measures of the mean of the firm’s

prospects) has no effect on our main estimates of interest, lending us confidence that our measure of political risk captures information about the second moment, but not the first moment.

Using a similar approach, we also construct measures of non-political risk (conditioning on non-political as opposed to political bigrams) and overall risk (counting only the number of synonyms for risk, without conditioning on political bigrams), and show that the information reflected in these measures differs from our measure of political risk in the way predicted by theory.

Thus, having bolstered our confidence that we are indeed capturing economically significant variation in firm-level political risk, we use it to learn about the nature of political risk affecting US listed firms. Surprisingly, most of the variation in political risk appears to play out at the level of the firm, rather than the level of (conventionally defined) sectors or the economy as a whole. Variation in aggregate political risk over time (time fixed effects) and across sectors (sector \times time fixed effects) account for only 0.81% and 7.50% of the variation in our measure, respectively. “Firm-level” variation drives the remaining 91.69%, most of which (71.82pp) is accounted for by changes over time in the assignment of political risk across firms within a given sector. Of course, part of this large firm-level variation may simply result from differential measurement error. However, all the associations between political risk and firm actions outlined above change little when we condition on time, sector, and sector \times time fixed effects, or if we increase the granularity of our definition of sectors. The data thus strongly suggest the large amount of firm-level (idiosyncratic) variation in our measure has real economic content.

To shed some light on the origins of firm-level variation in political risk, we provide detailed case studies of political risks faced by two illustrative firms over our sample period. These studies show the interactions between firms and governments are broad and complex, including the crafting, revision, and litigation of laws and regulations, as well as budgeting and procurement decisions with highly heterogeneous and granular impacts. For example, only a very small number of firms involved with power generation will be affected by new regulations governing the emissions of mercury from coal furnaces across state lines, or changing rules about the compensation for providing spare generation capacity in Ohio. Based on our reading of these transcripts, we find it quite plausible that the incidence of political risk should be highly volatile and heterogeneous, even within strictly defined sectors.

Our main conclusion from these analyses is that much of the economic impact of political risk is not well described by conventional models in which individual firms have relatively stable exposures to aggregate political risk (e.g., [Pastor and Veronesi \(2012\)](#); [Baker et al. \(2016\)](#)). Instead, firms considering their exposure to political risk may well be more worried about their relative position in the cross-sectional distribution of political risk (e.g., drawing the attention of regulators to their firms’ activities) than about time-series variation in aggregate political risk. Consistent with this interpretation, we also

find that this cross-sectional distribution has a fat right tail.

A direct implication of our findings is that the effectiveness of political decision-making may have important macroeconomic effects, not only by affecting aggregate political risk, but also by altering the identity of firms affected by political risk and the dispersion of political risk across firms. For example, if some part of the firm-level variation in political risk results from failings in the political system itself (e.g., the inability to reach compromises in a timely fashion), this may affect the allocation of resources across firms, and thus lower total factor productivity, in addition to reducing aggregate investment and employment (not to mention generating potentially wasteful expenditure on lobbying and political donations). Consistent with this view, we find that a one-percentage-point increase in aggregate political risk is associated with a 0.79-percentage-point increase in the cross-sectional standard deviation of firm-level political risk, suggesting the actions of politicians may indeed influence the dispersion of firm-level political risk.

After studying the incidence and effects of overall political risk, we turn to measuring the risks associated with eight specific political topics. To validate our topic-specific measures, we exploit the fact that firms that lobby any branch of the US government must disclose not only their total expenditure on lobbying, but also the list of topics this expenditure is directed toward. That is, lobbying disclosures uniquely allow us to observe a firm's reaction(s) to risks associated with specific political topics, and to create a mapping between specific political topics discussed in conference calls and the topics that are the object of the same firm's lobbying activities. Using this mapping, we are able to show that a one-standard-deviation increase in risk associated with a given political topic in a given quarter is associated with a 11% increase relative to the mean in the probability that a given firm will lobby on that topic in the following quarter. That is, a significant association exists between political risk and lobbying that continues to hold within firm and topic.

Although we do not interpret the associations between our measures of political risk and firm actions as causal, we believe the persistence of these associations conditional on time, firm, sector \times time, and (in the case of lobbying) topic and topic \times firm fixed effects, rule out many potentially confounding factors, and thus go some way toward establishing such causal effects of political risk.

Going beyond the narrow question of identification, a deeper challenge results from the fact that not all political risk is necessarily generated by the political system itself, but rather arises as a reaction to external forces (e.g., from political attempts to reduce the economic impact of a financial crisis). Although we have no natural experiments available that would allow us to systematically disentangle the causal effects of these different types of political risks on firm actions, we make a first attempt by studying three budget crises during the Obama presidency. These crises arguably created uncertainty about

the federal government’s ability to borrow and service its debts that resulted purely from politicians’ inability to compromise in a timely fashion. In addition, each episode is also described by unique terms that exclusively come into use in conference calls during the period of interest and not before: “debt ceiling,” “fiscal cliff,” and “government shutdown.” Using the frequency of use of these terms within a given transcript as an instrument for firm-specific political risk, we find that a one-standard-deviation increase in political risk generated these crises results in a 2.430-percentage-point increase (s.e.=0.937) in the probability that the firm lobbies the government on the the topic of “economic policy & budget” in the following quarter.

We make three main caveats to our analysis. First, all of our measures likely contain significant measurement error and should be interpreted with caution. Second, while showing statistically and economically significant associations between firm-level variation in our measures and firm actions, we do not claim this firm-level variation is more or less important than aggregate or sector-level variation. Third, all of our measures should be interpreted as indicative of risk as it is perceived by firm managers and participants on their conference calls. Naturally, these perceptions may differ from actual risk.

Our efforts relate to several strands of prior literature. An important set of studies documents that risk and uncertainty about shocks emanating from the political system affect asset prices, international capital flows, investment, employment growth, and the business cycle (Belo et al., 2013; Gourio et al., 2015; Handley and Limao, 2015; Kelly et al., 2016; Koijen et al., 2016; Besley and Mueller, 2017; Mueller et al., 2017).¹ In the absence of a direct measure, this literature has relied on identifying variation in aggregate and sector-level political risk using country-level indices, event studies, or the differential exposure of specific sectors to shifts in government contracting. Many recent studies rely on an influential index of US aggregate economic policy uncertainty (EPU) based on textual analysis of newspaper articles developed by Baker et al. (2016).² Relative to this existing work, we provide not just the first firm-level measure of political risk—uniquely allowing a meaningful distinction between aggregate, sector-level, and firm-level exposure—but also a flexible decomposition into topic-specific components.

Although our analysis partly corroborates key findings documented in previous research, for example, by showing aggregations of our firm-level political risk measure correlate closely with various sector-level and country-level proxies used in other papers, we also find such aggregations mask much of the variation in political risk, which is significantly more heterogeneous and volatile than previously thought. This

¹This literature has highlighted that political uncertainty is reflected in asset prices (Boutchkova et al. (2012); Brogaard and Detzel (2015); Bittlingmayer (1998); Voth (2002)).

²Jurado et al. (2015), Bachmann et al. (2013), and Giglio et al. (2016) propose measures of aggregate (political and non-political) uncertainty in the US economy. Caldara and Iacoviello (2016) propose an index of geopolitical uncertainty.

finding is in stark contrast to existing theoretical work that has typically viewed political risk as a driver of systematic but not idiosyncratic risk (Croce et al., 2012; Pastor and Veronesi, 2012, 2013; Born and Pfeifer, 2014; Fernandez-Villaverde et al., 2013; Drautzburg et al., 2017).

By contrast, our findings suggest political actions may affect the economic activity of firms in ways that are not well reflected in representative-agent models. For example, an increase in the dispersion of firm-level political risk may interact with financial or other frictions to reduce growth (Gilchrist et al., 2014; Arellano et al., 2016; Bloom et al., 2018). Or such a spike in the cross-sectional variation of political risk may reduce the efficiency of the allocation, and thus decrease total factor productivity (TFP), if part of the variation in firm-level political risk is inefficient (Hsieh and Klenow, 2009; Arayavechkit et al., 2017).

Another closely related strand of the literature studies the value of connections to powerful politicians (Roberts, 1990; Fisman, 2001; Johnson and Mitton, 2003; Khwaja and Mian, 2005; Jayachandran, 2006; Leuz and Oberholzer-Gee, 2006; Snowberg et al., 2007; Ferguson and Voth, 2008; Vidal et al., 2012; Cooper et al., 2010; Acemoglu et al., 2016, 2017).³ We contribute to this literature by showing that firms may lobby and cultivate connections to politicians in an attempt to actively manage political risk. The paper closest to our is Akey and Lewellen (2016), which shows that firms whose stock returns are most sensitive with respect to variation in EPU are more likely to donate to politicians.⁴

Finally, several recent studies in have adopted methods developed in computational linguistics and natural language processing. These studies tend to use pre-defined dictionaries of significant words to process source documents (Loughran and McDonald (2011); Baker et al. (2016)). By contrast, our approach aims to endogenously capture those word combinations that are indicative of political discourse about a given topic.⁵ In addition, whereas prior studies have relied on newspaper archives and corporate disclosures as source texts (Baker et al. (2016); Koijen et al. (2016); Wiesen and Wysocki (2015); Gentzkow and Shapiro (2010)), we introduce the idea that (transcripts of) conference calls provide a natural context to learn about the risks firms face and market participants' views thereof.

³In turn, politicians reciprocate by distributing favors in the form of bailouts (Faccio et al., 2006; Tahoun and Van Lent, 2016), reduced government oversight (Correia, 2014), more government contracts (Goldman et al., 2009; Tahoun, 2014), and reduced market competition (Benmelech and Moskowitz, 2010).

⁴A large literature documents that lobbying is pervasive in the US political system (Milyo et al., 2000), can affect policy enactment (Kang, 2016), and yields economically significant returns (De Figueiredo and Silverman, 2006). Arayavechkit, Saffie, and Shin (2017) develop a quantitative model of lobbying and taxation.

⁵Alternative text-mining approaches (e.g., Latent Dirichlet Allocation, LDA) enable automated topic classification. However, LDA-type methods are likely to lack the power to detect politics-related issues as a separate topic. Reflecting the possibly limited advance offered by more sophisticated methods, the literature in computational linguistics has documented that our simple, yet intuitive approach is remarkably robust (Ramos (2003); Mishra and Vishwakarma (2015)).

1 Data

We collect the transcripts of all 178,173 conference calls held in conjunction with an earnings release (hereafter “earnings conference call” or “earnings call”) of 7,357 firms listed in the United States between 2002 and 2016 from Thomson Reuters’ StreetEvents. During our sample window, firms commonly host one earnings call every fiscal quarter, thus generating roughly four observations per firm per year.⁶ Calls typically begin with a presentation by management, during which executives (e.g., the Chief Executive Officer or the Chief Financial Officer) share information they wish to disclose or further emphasize, followed by a question-and-answer (Q&A) session with market participants (usually, but not limited to, financial analysts). Our measure of political risk is constructed using the entire conference call.⁷

To obtain data on corporate lobbying, we take advantage of the Lobbying Disclosure Act of 1995, which requires lobbyists and lobbying firms to file their lobbying activities with the Clerk of the House of Representatives and the Secretary of the Senate.⁸ We rely on the Center for Responsive Politics (CRP), a nonpartisan not-for-profit research group that obtains these reports and standardizes the names of firms and a breakdown of the lobbying expenditures by issues or topics. Lobbying firms are required to provide a good-faith estimate, rounded to the nearest USD 10,000, of all lobbying-related income from each of their clients, as well as a list of topics on which each client lobbies. The Center assigns the value of zero to all those cases in which the lobby expenditure falls below the disclosure threshold. We then manually match the 80 issues from the disclosure forms to the eight topics our topic-based measure of political risk encompasses (see Appendix Table 1 for details). We also obtain data on campaign contributions by the Political Action Committees associated with our sample firms from the CRP. Table 1, Panel A, provides summary statistics.

We obtain data on government contracts for the period 2002 to 2016 from USAspending.gov, an official government website that provides these data under the Federal Funding Accountability and Transparency Act of 2006. We use primary contract awards and take the sum of the net value of all new contracts for a given firm and quarter in which the contract was signed. Using a fuzzy matching algorithm, we match firm names with Compustat firm names. Altogether, 2,695 of the 7,357 unique firms in our dataset receive federal contracts during our sample period.

⁶Firms are not mandated to host conference calls, but illustrative of their importance is the 2014 National Investor Relations Institute survey, which suggests 97% of investor relations officers report that their firms hold quarterly earnings calls. Firms provide access to their calls via live webcasting, and make transcripts and audio files available on their investors’ relations websites, public databases, and other websites aimed at investors (e.g., seekingalpha.com).

⁷In untabulated analysis, we find the average number of words spoken in our sample conference calls is 7,533. [Matsumoto et al. \(2011\)](#) obtain the start and end times of each portion of the call. They find a typical earnings conference call lasts for about 46 minutes, with on average 18 minutes for the managerial presentation and 28 minutes for the Q&A. These authors further show managers seek to alleviate pre-call uncertainty with lengthier conference calls.

⁸The Honest Leadership and Open Government Act of 2007 increased the filing frequency for lobby reports from semi-annually to quarterly.

For each firm-quarter or, if not available, firm-year, we obtain employment, investment, and basic balance-sheet (e.g., total assets) and income-statement (e.g., quarterly earnings) information from Standard and Poors’ Compustat. For a smaller set of firms, we also collect data on the firm’s projected capital expenditure for the following fiscal year from the I/B/E/S Guidance database. OptionMetrics provides firm-quarter-level implied volatility.⁹

Finally, we obtain stock price and return data from the Center for Research in Security Prices. The descriptive statistics, reported in Table 1, for the accounting and market data are generally consistent with those of previous studies.

2 Measuring Political Risk at the Firm Level

In this section, we introduce our firm-level measure of political risk. To separate measurement from interpretation, we begin by defining a measure of the share of the quarterly conversation between call participants and firm management that centers on risks associated with political topics. In a second step, we then argue this measure can be interpreted as a proxy for the political risk and uncertainty individual firms face.

2.1 Defining a measure of political risk

We begin with a simple objective: to measure the share of the conversation between analysts and firm management that centers on risks associated with political topics. Clearly, any topic that is raised during an earnings conference call will tend to be of some concern either for the firm’s management or its analysts, such that quantifying the allocation of attention between different topics is interesting in its own right.

Rather than a priori deciding on specific words associated with different topics, we distinguish political from non-political topics using a pattern-based sequence-classification method developed in computational linguistics (Song and Wu, 2008; Manning et al., 2008). Using this approach, we correlate language patterns used by conference-call participants to that of a text that is either political in nature (e.g., an undergraduate political science textbook) or indicative of a specific political topic (e.g., speeches by politicians about health care). Similarly, we identify the association with risk simply by the use of synonyms of the words “risk” and “uncertainty” in conjunction with this language.

⁹For European options, OptionMetrics first calculates the theoretical option price as the midpoint of the best closing bid and offer prices, and then computes the implied volatility by inverting the Black-Scholes formula. For American options, OptionMetrics obtains implied volatilities by applying a proprietary pricing algorithm based on the Cox-Ross-Rubinstein binomial tree model.

Specifically, we construct our measure of overall political risk by first defining a training library of “political” text, archetypical of the discussion of politics, \mathbb{P} , and another training library of “non-political” text, archetypical of the discussion of non-political topics, \mathbb{N} . Each training library is the set of all adjacent two-word combinations (“bigrams”) contained in the respective political and non-political texts (after removing all punctuation).¹⁰ We then similarly decompose each conference-call transcript of firm i in quarter t into a list of bigrams contained in the transcript $b = 1, \dots, B_{it}$.¹¹ We then count the number of occurrences of bigrams indicating discussion of a given political topic within the set of 10 words surrounding a synonym for “risk” or “uncertainty” on either side, and divide by the total number of bigrams in the transcript:

$$PRisk_{it} = \frac{\sum_b^{B_{it}} \left(1[b \in \mathbb{P} \setminus \mathbb{N}] \times 1[|b - r| < 10] \times \frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \right)}{B_{it}}, \quad (1)$$

where $1[\bullet]$ is the indicator function, $\mathbb{P} \setminus \mathbb{N}$ is the set of bigrams contained in \mathbb{P} but not \mathbb{N} , and r is the position of the nearest synonym of risk or uncertainty. The first two terms in the numerator thus simply count the number of bigrams associated with discussion of political but not non-political topics that occur in proximity to a synonym for risk or uncertainty (within 10 words). In our standard specification, we also weight each bigram with a score that reflects how strongly the bigram is associated with the discussion of political topics (the third term in the numerator), where $f_{b,\mathbb{P}}$ is the frequency of bigram b in the political training library and $B_{\mathbb{P}}$ is the total number of bigrams in the political training library. Our overall measure of the share of the conversation devoted to risk associated with political topics is thus the weighted sum of bigrams associated with political (rather than non-political) text that are used in conjunction with synonyms for risk or uncertainty.

This specification follows closely the most canonical weighting scheme used in the automated text-classification literature, where the two terms $1[b \in \mathbb{P} \setminus \mathbb{N}] \times f_{b,\mathbb{P}}/B_{\mathbb{P}}$ are commonly referred to as the bigram’s *inverse document frequency* interacted with its *term frequency* (Sparck Jones, 1972; Salton and McGill, 1983; Salton and Buckley, 1988). When more than two training libraries exist, the former generalizes to the more familiar form: $\log(\# \text{ of training libraries} / \# \text{ of libraries in which the bigram occurs})$. In this sense, (1) is a straight-forward application of a standard text-classification algorithm, augmented by our conditioning on the proximity to a synonym for risk or uncertainty, and a normalization with the length of the transcript. In robustness checks reported below, we experiment with a

¹⁰Previous research suggests text-classification results generally improve by applying n-grams (usually bigrams) of words as opposed to single words (unigrams) (Tan et al., 2002; Bekkerman and Allan, 2004).

¹¹As is standard in the literature, we remove all bigrams that contain pronouns, shortened pronouns, or two adverbs. We have also experimented with more involved procedures for preparing the text contained in the transcript, such as removing stop words and lemmatizing. However, we found these procedures did not substantially affect our results.

number of plausible variations of (1). Across all of these variations, we generally find this conventional approach yields the most consistent results.

Although we construct $PRisk_{it}$ using a weighted rather than a straight sum of bigrams in the numerator, we continue to interpret it as a measure of the *share* of the conversation devoted to risks associated with political topics, adjusted for the fact that some passages of text can be more or less related to politics. (Nevertheless, we also show below that our results are similar when we do not use this weighting.)

2.2 Defining additional measures of risk and sentiment

An advantage of this approach – combining pattern-based sequence classification with conditional word-counts – is that also lends itself to measuring the extent of conversation about topics that are related to political risk, but logically distinct from it, simply by modifying the conditioning information (1). We find it useful to construct two sets of such additional measures for use as control variables and in falsification exercises that corroborate and contrast the information content of $PRisk_{it}$.

The first two of these measures distinguish between different types of risk: Dropping the conditioning on political bigrams in (1) yields a simple measure of conversations about the overall degree of risk the firm faces – simply counting the number of synonyms for risk or uncertainty found in the transcript,

$$Risk_{it} = \frac{\sum_b^{B_{it}} 1[b \in \mathbb{R}]}{B_{it}}, \quad (2)$$

where \mathbb{R} denotes the same set of synonyms for risk or uncertainty used in the construction of (1). Similarly, we measure the share of the conversations centering on risks and uncertainties associated with non-political topics, $NPRisk_{it}$, by counting and weighting $\mathbb{N} \setminus \mathbb{P}$ rather than $\mathbb{P} \setminus \mathbb{N}$ in (1).

The second set of additional measures serves to disentangle information about the mean from information about the variance of political shocks: A major challenge to any measurement of risk is that innovations to the variance of shocks are likely correlated with innovations to their conditional mean. For example, a firm that receives news it is being investigated by a government agency simultaneously learns that it faces a lower mean (e.g. a possible fine) and higher variance (the outcome of the investigation is uncertain).

Following the same procedure as in the construction of $PRisk_{it}$, we are able to measure variation in the mean of the firm’s political shocks by again counting the use of political but not non-political bigrams, but now conditioning on proximity to positive and negative words, rather than synonyms of

risk or uncertainty:

$$PSentiment_{i,t} = \frac{1}{B_{it}} \sum_b^{B_{it}} \left(1[b \in \mathbb{P} \setminus \mathbb{N}] \times \frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \times \sum_{c=b-10}^{b+10} S(c) \right), \quad (3)$$

where $S(c)$ is a function that assigns a value of +1 if bigram c appears on a list of bigrams with positive sentiment provided by Loughran and McDonald (2011), a value of -1 if c appears on their list of bigrams with negative sentiment, and 0 otherwise (see Stone et al. (1966), for a discussion of early work). Frequently used positive and negative words include ‘good,’ ‘strong,’ ‘great,’ and ‘loss,’ ‘decline,’ and ‘difficult,’ respectively.^{12 13} (See Appendix Table 2 for details.) Using the same procedure we also calculate a measure of overall sentiment

$$Sentiment_{it} = \frac{\sum_b^{B_{it}} S(b)}{B_{it}}, \quad (4)$$

as well as a measure of non-political sentiment ($NPSentiment_{it}$), constructed by counting and weighting $\mathbb{N} \setminus \mathbb{P}$ rather than $\mathbb{P} \setminus \mathbb{N}$ in (3).

Taken at face value, these additional measures should proxy for the mean and variance of different types of shocks in a manner similar to, but logically distinct from $PRisk_{it}$. Although we use them primarily to corroborate the information content of $PRisk_{it}$, they may be of independent interest for a variety of other applications. To maintain focus, we relegate the majority of the material validating these additional measures to the appendix, and refer to it in the main text only when relevant. All measures are available on the authors’ websites.

2.3 Training libraries

Our measure of the share of the conversation devoted to risks associated with politics (1) differs from similar measures used in the previous literature in two important respects. First, it is constructed using text generated by decision makers within firms rather than newspaper articles or indicators from financial markets. Second, it does not require us to exogenously specify which words or word patterns may be associated with which topic. Instead, the only judgement we have to make is about training libraries—what text may be considered archetypical of discussions of a given political topic or non-political topics.

¹²We choose to sum across positive and negative sentiment words rather than simply conditioning on their presence to allow multiple positive words to outweigh the use of one negative word, and vice versa. Sentiment words are an order of magnitude more frequent in our conference call transcripts than synonyms for risk or uncertainty.

¹³One potential concern that has been raised with this kind of sentiment analysis is the use of negation, such as ‘not good’ or ‘not terrible’ (Loughran and McDonald (2016)). However, we have found the use of such negation to be exceedingly rare in our analysis, so that we chose not to complicate the construction of our measures by explicitly allowing for it.

In our applications, we show results using three alternative approaches to defining the political and non-political libraries (\mathbb{P} and \mathbb{N}). In the first, we use undergraduate textbooks, where the non-political library consists of bigrams extracted from a textbook on financial accounting (Libby et al., 2011), to reflect that earnings conference calls tend to focus on financial disclosures and accounting information. As the source for the bigrams in the corresponding political training library, we use Bianco and Canon’s textbook, *American Politics Today* (3rd ed.; Bianco and Canon (2013)).

In the second, we construct the non-political library by selecting from Factiva any newspaper articles published in the *New York Times*, *USA Today*, the *Wall Street Journal*, and the *Washington Post* on the subject of “performance,” “ownership changes,” or “corporate actions” during our sample period, and contrast it with a political training library derived from newspaper articles from the same sources on the subject of “domestic politics.”

In both cases, we also include all bigrams from the Santa Barbara Corpus of Spoken American English (Du Bois et al., 2000) as part of the non-political library to filter out bigrams that are specific to spoken language, such as “next question” or “we should break for lunch.” This source records a vast library of face-to-face conversations, on-the-job talk, classroom lectures, sermons, and so on, where we exclude a small part of this library that contains conversations related to politics.¹⁴

We will show both approaches yield similar results in terms of our analysis, although they identify slightly different bigrams as pivotal for political text. Whereas the textbook-based approach identifies bigrams such as “the constitution” and “interest groups” as most pivotal, the newspaper-based approach identifies more topical expressions such as “[health] care reform” and “president obama.”

In our preferred specification, we therefore use a hybrid of the two approaches. We first define \mathbb{P} and \mathbb{N} using the textbook-based training libraries, yielding 101,165 bigrams in the set $\mathbb{P}\setminus\mathbb{N}$. We then add the same number of bigrams from the newspaper-based approach (adding 87,813 bigrams that were not already in the set) and normalize the score of these additional bigrams ($f_{b,\mathbb{P}}/B_{\mathbb{P}}$) such that it is equal to the mean of the bigrams identified using only the textbook-based libraries.¹⁵

Finally, we obtain the list of synonyms for “risk,” “risky,” “uncertain,” and “uncertainty” from the Oxford dictionary (shown in Appendix Table 3). Because they are likely to have a different meaning in the context of conference calls, we exclude from this list the words “question,” “questions” (e.g., conference-call moderators asking for the next question), and “venture.” For a similar approach, see

¹⁴We exclude the following nine episodes: SBC004 (*Raging Bureaucracy*), SBC011 (*This Retirement Bit*), SBC012 (*American Democracy is Dying*), SBC019 (*Doesn’t Work in this Household*), SBC026 (*Hundred Million Dollars*), SBC030 (*Vision*), SBC032 (*Handshakes All Around*), SBC035 (*Hold My Breath*), and SBC038 (*Good Strong Dam*).

¹⁵Because the newspaper-based libraries are significantly longer than the textbook-based libraries, we chose this approach to ensure both sources of text receive equal weight. Simply adding the newspaper-based and textbook-based political libraries would largely collapse to using only the newspaper-based library, simply due to the different sizes of original texts.

Allee and DeAngelis (2015).

As a simple way of reducing reliance on a few bigrams with very high term frequency, we cap $PRisk_{it}$ at the 99th percentile. To facilitate interpretation, we also standardize with its sample standard deviation.

2.4 Validation

We next describe the output of our measure and verify it indeed captures passages of text that discuss risks associated with political topics. Table 2 shows the bigrams in $\mathbb{P}\setminus\mathbb{N}$ with the highest term frequency, $(f_{b,\mathbb{P}}/B_{\mathbb{P}})$, that is, the bigrams associated most strongly with discussion of political versus non-political topics and receiving the highest weight in the construction of $PRisk_{it}$. These bigrams are almost exclusively with strong political connotations, such as “the constitution,” “the states,” and “public opinion.” Appendix Figure 1 shows a histogram of these bigrams by their term frequency. It shows the distribution is highly skewed, with the median term frequency being 0.586×10^{-5} . This finding implies the top 120 bigrams listed in Table 2 (with scores ranging from 201.15×10^{-5} to 18.18×10^{-5}) are among the primary drivers of $PRisk_{it}$.

Table 3 reports excerpts of the 20 transcripts with the highest $PRisk_{it}$, a summary of the political risks discussed in the transcripts, and the text surrounding the top-scoring political bigram. All of these highest-scoring transcripts indeed contain significant discussions of risk associated with political topics. For example, the transcript with the highest score (Nevada Gold Casino Inc in September of 2008) features discussions of a pending ballot initiative authorizing an increase in betting limits, the potential impact of a statewide smoking ban, and uncertainties surrounding determinations to be made by the EPA. Other transcripts focus on uncertainty surrounding tort reform, government funding, legislation, and many other political topics.

The second half of the table (Panel B) shows only one false positive: a transcript of a call held by Piedmont Natural Gas that, in fact, does not contain a discussion of risks associated with any political topic. The reason it nevertheless has a relatively high score is that the transcript is very short—only six pages—and contains the one passage shown in column 5, which, although it contains bigrams from $\mathbb{P}\setminus\mathbb{N}$, does not relate to political risk. Reassuringly, all other (i.e., 19 out of 20) transcripts are correctly identified as containing long discussions of political risk relative to the length of the transcript (summarized in column 4).

Although our approach is designed to measure the share of the transcript, not the paragraph, containing discussion of political risks, the fact that the text surrounding the bigram with the highest $f_{b,\mathbb{P}}/B_{\mathbb{P}}$ (shown in column 5) also reliably identifies a passage of text within the transcript that contains

the discussion of one of the topics shown in column 4 is reassuring. The only exception is the transcript by Employers Holdings and Transcontinental in which these topics are identified within transcript by other high-scoring bigrams.

On two other occasions, as column 5 shows, the conditioning on proximity to synonyms produces apparently false positives: one in which the word “bet” is not meant to refer to risks associated with the ballot initiative but rather to betting limits, and another in which “government pressures” are mentioned in proximity to discussion of “currency risks.” Nevertheless, both snippets of text correctly identify discussions of risks associated with political topics. Accordingly, we show evidence below that this conditioning on synonyms for risk or uncertainty has economic content and on average improves the properties of our measure.

Having examined the workings of our pattern-based classifications, we next examine the properties of the measures they generated. Figure 1 plots the average across firms of our measure of overall political risk at each point in time, $1/N \sum_i PRisk_{it}$. The plot also highlights some important political and economic events, and plots the newspaper-based measure of economic policy uncertainty (EPU) constructed by Baker et al. (2016) for comparison. The two series have a correlation coefficient of 0.82 and thus visibly capture many of the same events driving uncertainty about economic policy. This high correlation is reassuring because both series are constructed using very different data sources and methodologies, but nevertheless yield similar results.¹⁶ It also suggests that, as one might expect, uncertainty about economic policy is a major component of the aggregate variation in political risks on the minds of managers and conference-call participants.

Further probing the variation in the mean of $PRisk_{it}$ over time, we might expect that part of the overall political risk firms face arises due to uncertainty about the identity of future decision makers. For example, Democrats may be more inclined than Republicans to pass tough environmental regulations. Elections should resolve some of the uncertainties about the actions of future decision makers, and thus increase and decrease aggregate political risk at regular intervals. Figure 2 shows results from a regression relating $PRisk_{it}$ to a set of dummy variables indicating quarters with federal elections (presidential and congressional), as well as dummies for the two quarters pre and post these elections. We can see political risk is significantly higher in the quarters in which elections are held and the quarters before, but falls off in the quarter after elections. This effect is most pronounced for presidential elections, when overall political risk tends to be 13.3% of a standard deviation higher (s.e.=0.016). Congressional

¹⁶For comparison, Appendix Figure 2 plots the average across firms of our measure of non-political risk ($NPRisk_{it}$), which comfortably is more strongly related to the CBOE stock market volatility index (VIX) (with a correlation of 0.846) than to EPU (with a correlation of 0.538). The reverse is true for the average across firms of $PRisk_{it}$, which is more strongly associated with EPU (with a correlation of 0.821) than with the VIX (with a correlation of 0.608); see Figure 1.

elections on average have a much smaller effect (2.1% higher, s.e.=0.010); see Appendix Table 4 for details. The relative size of these effects is again intuitive because presidential elections always also entail congressional elections and are thus arguably more decisive for the future political direction of the country than congressional elections alone.

Probing the variation of our measure across sectors (SIC divisions), we find that participants in conference calls of firms in the ‘finance, insurance & real estate’ sector on average spend the highest proportion of their time discussing risks associated with political topics, followed by the ‘construction’, and ‘transportation & communications’ sectors (see Panel A of Appendix Figure 3). By contrast, firms in the ‘retail trade’ sector have the lowest average $PRisk_{it}$. At the SIC-2-digit level, the sectors with the highest average $PRisk_{it}$ across firms include insurance carriers, producers of tobacco products, depository institutions, and construction firms (see Panel B of Appendix Figure 3). Overall, these means line up intuitively with parts of the economy that may be considered most dependent on government for regulation or expenditure. Figure 3 formalizes this insight by showing a positive and highly significant correlation between the mean $PRisk_{it}$ across firms in a given 2-digit sector and an index of regulatory constraints (Al-Ubaydli and McLaughlin, 2017), as well as the share of the sector’s revenue accounted for by federal government contracts.

To further probe the properties of our measure, we make use of historical episodes in which a particular political shock is associated with a unique word or expression that is used only during the period of interest, and not before. Arguably the best example is the term “Brexit.” Appendix Table 5 shows that the 954 firms that mention the term during their earnings call in the third quarter of 2016 exhibit a significant increase in their level of $PRisk_{it}$ (on average by 17.2% of a standard deviation) relative to the previous quarter.¹⁷ The same is true for firms that mention the words “trump” and “twitter” or “tweet” in the fourth quarter of 2016 (on average by 89.6% of a standard deviation).¹⁸

We next show $PRisk_{it}$ correlates significantly with realized and implied volatility of stock returns—a clear requirement for any valid measure of risk. Our main specification takes the form

$$y_{it} = \delta_t + \delta_s + \beta PRisk_{it} + \gamma X_{it} + \epsilon_{it}, \tag{5}$$

where δ_t and δ_s represent a full set of time and sector fixed effects, and the vector X_{it} always contains the log of the firm’s assets as a control for its size. Throughout, we use standard errors clustered by

¹⁷Using segment data from CapitalIQ, we also verify these firms do significantly more of their business in the UK. Regressing the firm’s percentage of total sales to the UK on the number of times the term “Brexit” is used in the third quarter of 2016 yields a coefficient of 0.28 (s.e.=0.05).

¹⁸For firms that mention these terms at least once, the average number of mentions is 6.15 for “brexit” and 6.4 for “trump” and “twitter,” or “trump” and “tweet.” Multiplying these numbers by the coefficients given in the table yields $6.15 \times 0.028=0.172$ and $6.40 \times 0.140=0.896$.

firm.¹⁹

Panel A of Table 4 uses implied stock return volatility, measured using 90-day at-the-money options (again standardized for ease of interpretation). Column 1 shows our most parsimonious specification where we regress this variable on $PRisk_{it}$ and the size control. The coefficient of interest is positive and statistically significant at the 1% level (0.056, s.e.=0.006), suggesting a one-standard-deviation increase in political risk at the firm level is associated with a 0.06-standard-deviation increase in the firm’s stock return volatility. Column 2 shows that much of this association is driven by the time-series dimension: when adding the mean of $PRisk_{it}$ across firms at each point in time as a control, the coefficient of interest drops by about one-third (0.034, s.e.=0.006), but remains statistically significant at the 1% level. The coefficient on the mean itself suggests a one-standard-deviation increase in the time series (which is factor 6.74 smaller than in the panel) is associated with a 0.262-standard-deviation increase (s.e.=0.004) in volatility, a number very similar to that documented in previous research (Baker et al., 2016). Columns 3 and 4 build up to our standard specification by adding time and sector fixed effects. Throughout, the estimates of β remain highly statistically significant (0.025, s.e.=0.005 in column 4). It also remains statistically significant but falls to 0.016 (s.e.=0.006) once we go from sector fixed effects to a more demanding specification with firm and CEO fixed effects (column 6). Panel B shows parallel results for the larger set of firms for which we can measure realized (rather than implied) volatility, that is, the standard deviation of the firm’s daily stock holding return (adjusted for stock splits and dividends) during the quarter.

Our measure of political risk at the firm level is thus significantly correlated with stock market volatility even when focusing only on within-time-and-sector variation, bolstering our confidence that $PRisk_{it}$ indeed captures a type of risk. The fact that this association is smaller within time and sector than in the time series is interesting, because it suggests part of the strong association between aggregate political risk and aggregate stock market volatility may be driven by reverse causality, where, for example, politicians entertain reform—and thus create political risk—as a response to deteriorating macroeconomic conditions. To the extent that introducing time and sector effects rules out this kind of confounding effect at the macroeconomic level, we hope the smaller estimates we obtain in the within-time-and-sector dimension stimulate future efforts to isolate the causal effect of political risk on volatility and other outcomes (e.g., using a natural experiment that generates exogenous variation in

¹⁹To corroborate our choice of standard errors, Appendix Figure 4 shows the results of a falsification exercise in the spirit of Fisher’s randomization inference procedure, where we repeatedly assign the $PRisk_{it}$ to a randomly selected other firm with replacement. The figure shows a histogram of t-statistics on the estimated coefficient on $PRisk_{it}$ across 500 random assignments. The t-statistics are centered around zero, with no noticeable tendency for positive or negative estimates. Reassuringly, the rates of false positives and negatives are about 2.5%. Appendix Table 6 shows alternative standard errors clustered by sector and time.

political risk). However, part of the difference in the size of coefficients is also likely due to differential measurement error. We discuss this possibility in more detail below.

The conclusion from this first set of validation exercises is that transcripts with the highest $PRisk_{it}$ indeed center on the discussion of political risks and that the time-series and cross-sectional variations of our measure line up intuitively with episodes of high aggregate political risk and with sectors that are most dependent on political decision-making. Consistent with these observations, $PRisk_{it}$ correlates significantly with firms' stock volatility.

3 Managing Political Risk

Next, we further probe the validity of our measure by examining how it correlates with actions taken by the firm. The theoretical literature makes three broad sets of predictions. First, standard models of investment under uncertainty predict that an increase in any kind of risk, and thus also an increase in the firm's political risk, should decrease firm-level investment and employment growth (e.g., Pindyck (1988); Bernanke (1983); Dixit and Pindyck (1994); Bloom et al. (2007)).²⁰ Second, a large literature in political economy predicts that firms have an incentive to "actively" manage political risk by lobbying and donating to politicians (Tullock, 1967; Stigler, 1971; Peltzman, 1976). Third, active management of political risks should be concentrated among large but not small firms due to free-rider problems (Olson, 1965).

The three panels of Table 5 test each of these predictions in turn. Panel A reports the association between $PRisk_{it}$, again standardized by its standard deviation, and corporate investment and hiring decisions. The capital investment rate, $I_{i,t}/K_{i,t-1}$, measured quarterly, is calculated recursively using a perpetual-inventory method as described in Stein and Stone (2013). For a smaller set of firms, we can also measure the percentage change in projected capital expenditure, $\Delta capex_{i,t}/capex_{i,t-1}$, as the change (relative to the previous quarter) in the firm's guidance for total capital expenditure for the next fiscal year. Net hiring, $\Delta emp_{i,t}/emp_{i,t-1}$, is the change in year-to-year employment over last year's value.^{21,22} All specifications are in the same form as (5), always including time and sector fixed

²⁰In macroeconomic models, increases in aggregate risk may increase or decrease aggregate investment, because of general equilibrium effects on the interest rate (precautionary savings; see, e.g., Fernández-Villaverde et al. (2015) and Hassan and Mertens (2017)). However, this ambiguity usually does not exist at the firm level (i.e., conditional on a time fixed effect). In models with adjustment costs, a firm that faces increases in firm-level risk should always decrease its investment relative to another firm that does not experience such an increase. (In the absence of adjustment costs this need not be the case, see Oi (1961); Hartman (1972); Abel (1983).)

²¹Because these data on investment, capital expenditure, and employment are notoriously noisy, we winsorize each of these variables following the same procedure as in Stein and Stone (2013).

²²Here, again, the number of observations is smaller because employment data are only available at the annual frequency. In all specifications with a dependent variable measured at the annual frequency, we take an arithmetic mean of $PRisk_{it}$ across all transcripts of a given firm and year.

effects, as well as controlling for the log of the firm’s assets. The coefficients in columns 1 to 3 suggests a one-standard-deviation increase in political risk is associated with a 0.159-percentage-point decrease in a firm’s capital investment rate (s.e.=0.041), a 0.338-percentage-point decrease in its planned capital expenditure for the following year (s.e.=0.120), and a 0.769-percentage-point decrease in its employment growth rate (s.e.=0.155). Whereas the former coefficient is relatively small (corresponding to a 1.4% decrease relative to the sample mean), the latter two coefficients correspond to economically large decreases of 28.7% and 11.5% relative to the sample mean, respectively.^{23 24}

Across the board, these results are suggestive of firms’ reactions to risk, where firms retrench hiring and investment when faced with heightened political risk. They are also consistent with the findings by Baker et al. (2016), who already document a negative relation between their measures of aggregate economic policy uncertainty and firm-level investment rates and employment growth. (Here we find the same pattern, even after controlling for time fixed effects.) Also consistent with this prior work, column 4 shows a much weaker and statistically insignificant association between $PRisk_{it}$ and sales growth. As argued in Baker et al. (2016), a smaller effect on sales is again consistent with the predictions of the real options literature: larger short-run effects of risk on hard-to-reverse investments in physical and human capital than on short-run output growth.

Panel B examines the degree to which firms affected by political risk also actively engage in the political process. Columns 1-3 study donations on behalf of the firm to politicians. We find a significant association between $PRisk_{it}$ and the dollar amount of campaign donations (column 1) as well as the number of politicians who receive contributions to their election campaigns from the firm (column 2). These associations are economically meaningful, as a one-standard-deviation increase in political risk is associated with a 8.7% increase in the total amount donated to politicians (s.e.=0.018) and an increase in the number of donation recipients of 0.462 (s.e.=0.118), representing a 17% increase relative to the mean of 2.73 recipients. Column 3 examines whether political risk may spur firms to develop ties with both major political parties at the same time, using $Hedge_{it}$, which is an indicator variable that captures those instances wherein firms donate similar amounts to both Democrats and Republicans.²⁵ Our intuition is that increases in political risk raise the benefit of having established connections with both parties. Consistent with this intuition, we find that as political risk increases, so does the likelihood of the firm “hedging” its political ties. In column 4, we turn to the firm’s overall lobbying expenditure,

²³Because changes in employment are measured at the annual frequency, we show contemporaneous correlations between $PRisk_{it}$ and the outcomes in Panel A. In Panel B, where all outcomes are at the quarterly frequency, we show correlations at the first lag.

²⁴Consistent with this pattern, we generally find that associations with firm-level outcomes are larger when aggregate outcome variables to the annual frequency, as also shown in columns 1 and 3 of Appendix Table 13.

²⁵Specifically, if the ratio of donations to Republicans over donations to Democrats is between the 25th and 75th percentile of the sample.

regressing the natural logarithm of one plus the dollar amount of lobby expenditure on $PRisk_{it}$. The estimate (0.186, s.e.=0.027) suggests a one-standard-deviation increase in political risk is associated with a 18.6% increase in the amount of lobbying expenditures.

Taken together, these results are consistent with the view that $PRisk_{it}$ indeed captures variation in political risk: firms more exposed to it retrench hiring and investment to preserve option value, and actively engage in the political system to mitigate these risks. If this interpretation is correct and firms actively manage political risk by forging ties with politicians and lobbying them, we might expect these associations to be stronger for large firms, which internalize more of the gain from influencing political decisions than small firms (Olson, 1965) and have the resources to sway political decisions at the federal or state level. Panel C of Table 5 shows that, indeed, predominantly larger firms donate to politicians in the face of political risk, whereas smaller firms that have worse prospects of actively influencing political decisions react with more vigorous retrenchment of employment and investment (the latter statistically significant only at the 10% level).²⁶

Mean vs. variance of political shocks. Having established that $PRisk_{it}$ correlates with firm actions in a manner highly indicative of political risk, we next introduce controls for news about the mean of political and non-political shocks, comparing the information contained in $PRisk_{it}$ with that contained in our measure of political sentiment ($PSentiment_{it}$) and in other controls for the firm’s prospects.

To corroborate that $PSentiment_{it}$ indeed contains information about the mean of political shocks, we follow steps similar to those above, showing that transcripts with the most positive (negative) $PSentiment_{it}$ indeed contain significant discussions of positive (negative) news about legislation, regulation, and government spending (see Appendix Tables 7 and 8). For example, the transcript with the most negative $PSentiment_{it}$ (Arctic Glacier in May of 2009) features a lengthy discussion of antitrust action by the department of justice against the firm, while the transcript with the most positive political sentiment (Central Vermont Public Service in May of 2006) anticipates advantageous changes to the regulation of electricity prices in Vermont. Consistent with these examples, we also find that firms tend to experience significantly positive stock returns in quarters when $PSentiment_{it}$ is high. Appendix Table 9 shows additional validation exercises.

The primary concern with our interpretation of the results in Table 5 is that firms with high $PRisk_{it}$ may simultaneously also receive bad news associated with political events (and vice versa), and that failing to control for variation in the mean of the firm’s political shocks may bias our estimates of the association between $PRisk_{it}$ and firm actions. Indeed, we find that the correlation between $PRisk_{it}$

²⁶This latter result is consistent with the predictions of Gilchrist et al. (2014), where firm-level risk affects macroeconomic aggregates due to financial frictions that are more severe for small than for large firms.

and $PSentiment_{it}$ is negative (-0.08), so that news about higher political risk does tend to arrive when firms have more negative sentiment about politics. Nevertheless, Table 6 shows no evidence of omitted variable bias in our estimates. Columns 1 and 5 replicate our standard specification for comparison. Column 2 shows that adding $PSentiment_{it}$ as an additional control does not have a perceptible effect on the coefficient of interest for any of the six outcome variables shown. In each case, the change in the coefficient is smaller than one standard error.

As expected, firms tend to invest and hire significantly more when they are more optimistic about politics (positive sentiment). Similarly, firms that are more optimistic about their political prospects also tend to invest significantly more in lobbying and political donations.

A related potential concern with our measure of political risk is that managers' incentives to discuss risks associated with political topics might vary over time. For example, they may have an incentive to blame politicians for bad performance by 'cheap talking' more about political risks whenever performance is bad. To test for this possibility, columns 3 and 7 add a control for the firm's overall sentiment ($Sentiment_{it}$). Similarly, columns 4 and 8 add two proxies for the firm's recent performance: its pre-call stock return, accumulated during the seven days prior to the earnings-related conference call, and a conventional measure for the earnings surprise.²⁷ Again, these variations have little to no effect on our estimates of the association between $PRisk_{it}$ and the firm's actions. We thus find no evidence that managers' incentives to blame political risks for bad performances affect our results.

Taken together, these results bolster our confidence that $PRisk_{it}$ correctly identifies variation in the second moment (risk), rather than merely the expected realization of political shocks.

Falsification exercises. We next conduct a series of falsification exercises comparing the information contained in $PRisk_{it}$ with that in our measures of non-political risk ($NPRisk_{it}$) and overall risk ($Risk_{it}$). The results are shown in Table 7. First, all kinds of risk, whether political or non-political, should be negatively associated with investment and hiring. When we add $NPRisk_{it}$ to the specification with investment as a dependent variable, we find exactly this pattern (column 2 in Panel A – all specifications now also control for $PSentiment_{it}$). The coefficient on $NPrisk_{it}$ is negative and statistically significant (-0.256, s.e.=0.043), whereas the one on $PRisk$ falls in absolute terms but retains its negative sign and statistical significance (-0.082, s.e.=0.042).²⁸ The same pattern, albeit with a much smaller change

²⁷Consistent with many prior studies, we define earnings surprise as earnings per share before extraordinary items minus earnings per share in the same quarter of the prior year, scaled by the price per share at the beginning of the quarter (Ball and Bartov, 1996).

²⁸Since both variables are standardized, the magnitudes of the two coefficients are not directly comparable to each other and should not be interpreted to mean that $NPRisk_{it}$ is more strongly associated with outcomes than $PRisk_{it}$. The standard deviation of $NPRisk_{it}$ is about factor 5 larger at the quarterly frequency than that of $PRisk_{it}$, so that its coefficients are mechanically inflated.

in the size of the coefficient on $PRisk_{it}$, holds for employment growth (column 5), suggesting both measures indeed contain information about risk.

Second, if firms indeed retrench hiring and investment due to *risks* associated with political topics, and not for other reasons, the association between $PRisk_{it}$ and these outcomes should be significantly attenuated when we control for overall risk. We find this pattern in columns 3 and 6 of Panel A, where $Risk_{it}$ reduces the negative association between $PRisk_{it}$ and these outcomes.

Third, firms should lobby and donate to politicians only to manage *political* risk, and not other forms of risk that are unrelated to politics. Consistent with this prediction, Panels B and C show $PRisk_{it}$ dominates $NPRisk_{it}$ and $Risk_{it}$ when predicting expenditures on lobbying and donations, as well as the other outcomes proxying for active management of political risk. Neither of the two measures of non-political and overall risk are significantly associated with any of these outcome variables, whereas the coefficient on $PRisk_{it}$ remains stable and highly statistically significant.

We view these contrasting results for active and passive forms of management of political risk (Panel A vs. Panels B and C) as strongly supportive of our interpretation that $PRisk_{it}$ indeed measures the extent of political risk a given firm faces.

The overall conclusion from our falsification exercises is that $PRisk_{it}$ is indeed a valid proxy for firm-level political risk: it meaningfully identifies transcripts that center on the discussion of political risk; its time-series and cross-sectional variation line up intuitively with episodes of high aggregate political risk and with sectors that are most dependent on political decision-making; it correlates with firm actions in a manner highly indicative of political risk; and its logical components (risk and political exposure) both serve their intended purpose—significantly identifying risks associated with political topics.

Choice of training libraries and alternative implementations of $PRisk_{it}$. Before using our measure to study the nature of political risk faced by firms listed in the United States, we discuss alternative implementations of $PRisk_{it}$. Conditional on the structure given in (1), which is a simple adaptation of existing methods in computational linguistics, the only judgment we made is in our choice of training libraries. In addition to our standard specification, which combines materials from textbooks, newspapers, and the Santa Barbara Corpus of Spoken American English, we also experimented with specifications that relied exclusively on textbooks or newspapers. In each case, we judged the quality of results based on an internal audit study, where we read the 50 transcripts with the highest and lowest scores, and manually measured the share of their contents that focused on risks associated with political topics. In addition, we checked the 600 political bigrams with the highest term frequencies for plausible links to political topics. In the course of this audit study, we quickly determined adding the Santa

Barbara Corpus of Spoken American English to the non-political library was always essential. Moreover, both the newspaper-based and the textbook-based approaches yielded surprisingly similar sets of top-50 transcripts, although both approaches yielded somewhat noisier results than our preferred specification. The correlation of the two alternative measures with $PRisk_{it}$ are 0.663 and 0.970, respectively (see Appendix Table 10). Appendix Table 11 replicates some of the key findings of the paper with these alternative measures.²⁹

Beyond the choice of training libraries, we also experimented with two other specifications. In the first, we dropped the weight $\frac{f_{b,P}}{B_P}$ from (1). Doing so did not fundamentally alter the sorting of transcripts generated (the correlation with $PRisk_{it}$ is .759), but led to a noticeable deterioration in its correspondence with the sorting obtained from our manual reading of transcripts. In the second, we dropped the pattern-based classification algorithm altogether and instead constructed a dummy variable (EPU_{it}) that equals 1 if the transcript contains a combination of words specified by (Baker et al., 2016, p. 1599), that is, if the transcript contained at least one term from each of the following three set of terms: “uncertain”, “uncertainties”, “uncertainty”; “economic” or “economy”; and “congress,” “deficit,” “federal reserve,” “legislation,” “regulation,” “regulatory,” “the fed,” or “white house.” Although this simpler measure is directionally still correlated with outcomes in the same way as $PRisk_{it}$, it appears to contain much less information, as shown in Appendix Tables 11 and 12.

4 Firm-level Political Risk

Having bolstered our confidence that $PRisk_{it}$ indeed captures political risk, we now use it to learn about the nature of political risk faced by firms and establish new stylized facts.

A notable feature of the associations between $PRisk_{it}$ and corporate outcomes, as documented in Tables 4 and 5, is that they all hold even when we condition on time and sector (at the SIC 2-digit level) fixed effects. This finding may be somewhat surprising given a focus in the literature on aggregate political risk that emanates from national politics and has relatively uniform impacts within sector (e.g., Pastor and Veronesi (2012)).

To probe the relative contributions of aggregate, sectoral, and firm-level political risk, we conduct a simple analysis of variance—asking how much of the variation in $PRisk_{it}$ is accounted for by various sets of fixed effects. The striking finding from this analysis, reported in column 1 of Table 8, is that time fixed effects—and thus the time-series variation of aggregate political risk shown in Figure 1—account

²⁹Another, completely different, approach would be to manually select passages of transcripts that focus on risks associated with political topics, and then use these manually selected passages as the political training library. We decided against this approach because its replicability is limited and for inducing a backward-looking bias by only identifying political risks of the same nature as those that preoccupied firms in the pre-sample.

for only 0.81% of the variation. Sector fixed effects (at the SIC 2-digit level) and the interaction of sector and time fixed effects only account for an additional 4.38% and 3.12%, respectively. This finding suggests most of the variation in $PRisk_{it}$ (91.69%) is within sector and time. Put differently, most of the variation in political risk reflected in our measure plays out at the level of the firm, rather than at level of the sector or the economy as a whole. For lack of a better term, we henceforth refer to this within-sector-and-time variation as “firm-level” or “idiosyncratic” variation in political risk. Although the two terms are often used synonymously in the literature, we prefer the former because it avoids confusion with the concept of non-systematic risk in the finance literature.³⁰

Further decomposing this firm-level variation, we find that permanent differences across firms in a given sector (i.e., firm-sector pair fixed effects) account for nearly one quarter (19.87%) of this variation, whereas changes over time in the assignment of political risk across firms within a given sector account for the remainder (i.e., the remaining 71.82% not explained by time or firm fixed effects).³¹

Perhaps surprisingly, these conclusions do not change substantially when we use more finely measured sector fixed effects. Repeating the steps of our decomposition with 407 SIC-4-digit sectors (column 3 of Table 8) assigns 16.82% to permanent differences across firms within sector and 61.51% to the residual (i.e., changes over time in the assignment of political risk across firms within a given sector).³²

Taken at face value, these results are at odds with the conventional view that political events have relatively uniform impacts across firms in a developed economy, where we think of regulatory and spending decisions as affecting large groups of firms at the same time. Instead, our decomposition suggests that, even among US listed firms, such decisions have differential impacts among subsets of firms, and that the identity of the firms most affected by political risk changes considerably over time; that is, when facing political risk, firms may be considerably more concerned about their position in the cross-sectional distribution (e.g., increased scrutiny by regulators of their activities) than about variation in the time series (e.g., elections or large-scale reforms).³³

Although suggestive, the results from our variance decomposition admit other interpretations. For instance, part of the large firm-level variation might simply be due to differential measurement error that makes firm-level variation harder to pick up than aggregate or sector-level variation. However,

³⁰However, we show below that the two concepts are quantitatively almost identical in our application, because very little of the firm-level variation appears to be explained by heterogeneous loadings on aggregate political risk.

³¹This large within-firm-and-time variation in political risk may partly explain why other studies have found a large amount of firm-level productivity risk that is not explained by industry- or economy-wide factors (Castro et al., 2010).

³²Of course, this residual mechanically disappears in the limit when each firm is assigned to its own sector. Nevertheless, the point remains that variation at the level of sectors, defined at conventional levels of granularity, does not absorb most of the variation in $PRisk_{it}$.

³³Consistent with this interpretation, Akey and Lewellen (2016) also find little persistence in firm’s “policy sensitivity” across election cycles, where firms are defined as “policy sensitive” if their monthly stock returns co-move significantly with the EPU measure in the 18 months prior to an election cycle. That is, the loadings of firms’ stock returns on aggregate political risk (EPU) appear to be changing across election cycles.

the highly significant associations between $PRisk_{it}$ and corporate outcomes, as documented in Tables 4 and 5, strongly suggest this variation nevertheless has economic content. In Figure 4, we take this one step further by showing the associations between $PRisk_{it}$ and investment, planned capital expenditure, and employment growth, respectively, all change very little when we supplement our time and sector fixed effects (column 1) with the interaction of sector and time fixed effects (column 2), as well as as fixed effects for each firm-sector pair (column 3).³⁴ For example, the correlation between $PRisk_{it}$ and employment growth is -0.769 (s.e.=0.155) in column 1 and -0.772 (s.e.=0.186) when we add firm-sector and sector \times time fixed effects in column 3. (As before, this pattern is largely invariant to using more granular definitions of sectors; see Appendix Table 14.) Our results thus suggest the large amounts of firm-level variation in political risk have real meaning and are not just an artifact of measurement error.

Although we cannot in general quantify the degree of measurement error contained in different dimensions of $PRisk_{it}$, it is possible to do so under some further assumptions. Suppose for example that true political risk follows a first-order auto-regressive process, and that $PRisk_{it}$ measures this true political risk with classical (i.i.d.) measurement error. If we could identify a valid instrument for $PRisk_{i,t-1}$ we could then back out the share of its variation consisting of measurement error by comparing the OLS and IV coefficients. Table 9 shows three such attempts, Panel A for the overall variation in $PRisk_{it}$, Panel B for its firm-level component. Column 1 shows the OLS estimates of the autocorrelation in $PRisk_{it}$. In column 2 we instrument $PRisk_{i,t-1}$ using an alternative measure of political risk constructed by applying (1) to the ‘management discussion and analysis’ sections of the firm’s annual 10K filings. Under the assumption that this alternative $PRisk10K_{it}$ is also an unbiased measure of true political risk, and that measurement error is uncorrelated between the two measures, the IV estimates shown in column 2 are unbiased. Using this estimate, we calculate that 48.5% (s.e.=1.8%) of the overall variation and 53.8% (s.e.=2.5%) of the firm-level variation in $PRisk_{it}$ consists measurement error, while the remaining variation reflects true political risk.³⁵ Columns 3 and 4 repeat the same calculations using the second lags, $PRisk10K_{i,t-2}$ and $PRisk_{i,t-2}$, as instruments, respectively. Across all of these specifications, the share of variation accounted for by measurement error is about four percentage points higher in firm-level variation than in the overall variation.

³⁴Consistent with these results, the unconditional correlations between $PRisk_{it}$ and these outcome variables are very similar. They are -0.162 (s.e.=0.043) for investment, -0.347 (s.e.=0.121) for planned capital expenditure, and -0.806 (s.e.=0.149) for employment growth. Conditioning on more granular variation thus generally has little effect on these estimates. See Appendix Table 14.

³⁵Appendix Table 13 shows that the correlations between $PRisk10K_{it}$ and firm-level outcomes are similar, but less pronounced and less statistically significant than those with (annualized) $PRisk_{it}$. We believe this pattern may be due to the fact that 10K disclosures are highly scripted and tend to have higher disclosure thresholds than conference calls. If 10K’s indeed disclose only severe and longer-term risks, it is likely that our instrumentation strategy isolates more persistent elements of the true underlying political risk, so that the estimates of measurement error in Table 9 may be more appropriately interpreted as upper bounds of the true measurement error.

Although we interpret these results with due caution, they suggest that the implied measurement error in the firm-level dimension is not dramatically higher than in the overall variation. Moreover, it is comforting that these shares of measurement errors are very similar to the degree of measurement error found in other firm-level variables constructed from accounting data, such as the measures of TFP constructed by [Bloom et al. \(2018\)](#) and [Collard-Wexler \(2011\)](#).

Another possibility is that the large amounts of firm-level variation in $PRisk_{it}$ might simply be driven by heterogeneous exposure to aggregate political risk. To probe this possibility, we construct a “political risk beta” for each firm by regressing its daily stock return on Baker, Bloom, and Davis’ daily EPU_t , and then include the interaction of this political risk beta with the mean across firms of $PRisk_{it}$ in our analysis of variance.³⁶ Specifically, we include it as a control in addition to the full set of time, sector, and sector \times time fixed-effects interactions. We find the coefficient on this interaction (not shown) is statistically indistinguishable from zero and accounts for less than a hundredth of the firm-level variation in overall political risk, suggesting it is not well described by a model in which firms have stable heterogeneous exposures to aggregate political risk.

Consistent with this result, column 2 of Table 10 shows the association between $PRisk_{it}$ and stock return volatility remains almost unchanged when we control for such heterogeneous exposure to aggregate political risk. Column 3 allows for time variation of firms’ political risk beta on a two-year rolling window interacted with the mean across firms of $PRisk_{it}$. Here, too, we find the coefficient on the interaction is statistically insignificant whereas the coefficient on $PRisk_{it}$ remains unchanged and highly statistically significant, thus suggesting any information reflected in these alternative measures is subsumed in $PRisk_{it}$.

Alternatively, part of the variation in firm-level political risk could simply reflect variation in government contracts awarded to different firms. To assess this possibility, in columns 4 and 5, we add controls for the log of one plus the dollar amount the firm has outstanding in government contracts. Including this variable, or its interaction with the mean across firms of $PRisk_{it}$, again has little effect on the coefficient of interest, suggesting variation in current government contracts is also not the primary driver of firm-level political risk. (Although, of course, concerns about the future allocation of government contracts might well be.) Appendix Table 15 shows parallel results using all the corporate outcomes studied in Table 5 as dependent variables.

To summarize, the main conclusion from this analysis is that the incidence of political risk across firms is far more volatile and heterogeneous than previously thought. Much of the economic impact of

³⁶We get the same results when we construct these betas purely based on the sum of $PRisk_{it}$ across firms. We prefer to use EPU_t in this instance because it is available at the daily (rather than quarterly) frequency.

political risk plays out within sector and time and is not well described by a model in which individual firms have relatively stable exposures to aggregate political risk. Instead, a surprisingly large share of the variation in political risk is accounted for by changes over time in allocation of political risk across firms within a given sector. That is, firms may be more concerned about their relative position in the cross-sectional distribution of political risk than about time-series variation in aggregate political risk.

We next elaborate on the macroeconomic implications of this finding before turning to two case studies that further illustrate the nature of the firm-level variation in political risk.

4.1 Macroeconomic effects of firm-level political risk

Much of the academic debate on the effects of political risk has focused on the idea that rises in aggregate political risk may reduce the average firm’s investments in human and physical capital (Baker et al., 2016; Fernández-Villaverde et al., 2015). The economically significant variation in firm-level political risk we document above suggests that the effectiveness of political decision making may, in addition, affect macroeconomic outcomes in more subtle ways, even when aggregate political risk is held constant.

First, by affecting firms’ investment and hiring decisions, firm-level variation in political risk should induce firm-level variation in measured total factor productivity. That is, firm-level political risk may in fact be a root cause of the kind of idiosyncratic productivity risk that has been the object of an active literature studying the microeconomic origins of aggregate fluctuations. Different branches of this literature have argued that idiosyncratic productivity shocks may propagate by impacting the actions of upstream and downstream producers, resulting in aggregate fluctuations (Gabaix, 2011; Acemoglu et al., 2012); and that spikes in idiosyncratic productivity risk may reduce aggregate economic growth if firms face financial or other frictions (Gilchrist et al., 2014; Arellano et al., 2016; Bloom et al., 2018).

Second, going beyond the effects of idiosyncratic risk studied in this literature, our finding that the allocation of political risk across firms is highly volatile and heterogeneous also suggests that it may result in an additional misallocation of resources across firms that lowers aggregate total factor productivity (Hsieh and Klenow, 2009; Arayavechkit et al., 2017).

To illustrate this channel, consider a simple model in which a unit mass of firms produce output using capital, $Y_{it} = K_{it}^\alpha$, with $\alpha < 1$ and $\int K_{it} di \equiv \bar{K}_t$. Capital investment decisions are made one period in advance subject to adjustment costs. In addition, assume that each firm faces uncertainty about some political decision that affects its profits; and that this uncertainty makes it privately optimal to reduce the level of investment so that $K_{it} = K^* e^{-b(\sigma_t + \sigma_{it})}$, where b is some positive constant and σ_t and σ_{it} are the aggregate and firm-level components of political risk, respectively. Both components are known to the firm, and the dispersion of political risk across firms follows a normal distribution,

$\sigma_{it} \sim N(b\frac{\Sigma_t^2}{2}, \Sigma_t)$. For the sake of argument, let us also assume that this political risk is unrelated to economic fundamentals and originates exclusively from failings in the political system itself (e.g., an inability to reach compromise in a timely manner), so that the socially optimal level of investment is $K_{it} = K^*$.

Within this model, the conventional concern is that aggregate political risk depresses \bar{K}_t below its optimal level and that spikes in aggregate political risk may cause business cycles by inducing the average firm to temporarily lower investment. (Taking our results in Table 5 at face value, we are inclined to add socially wasteful lobbying activities and donations to politicians to this list.)

Solving the model, we can show that in addition to these aforementioned effects, the dispersion in political risk across firms lowers total factor productivity: $Y_t = e^{-\phi\Sigma_t^2} \bar{K}_t^\alpha$, where $\phi = \frac{1}{2}b^2(1-\alpha)\alpha > 0$. That is, the mere existence of dispersion of political risk across firms directly lowers aggregate total factor productivity and output, even if we hold constant the aggregate capital stock. In addition, any temporary increase in this dispersion causes a recession by causing total factor productivity to fall.

To summarize, our results suggest that the effectiveness of political decision-making may have important macroeconomic effects not only by affecting aggregate political risk, but also by altering the identity of firms affected by political risk and the dispersion of firm-level political risk over time.³⁷

To probe this latter possibility, we again project $PRisk_{it}$ on sector, time, and the interaction of time and SIC 2-digit sector fixed effects, calculate their cross-sectional standard deviation at each point in time, and plot this variation in the top panel of Figure 5 as a proxy for the time-series variation in Σ_t . For comparison, the figure also plots the average across firms of $PRisk_{it}$ (corresponding to σ_t in the model). The figure shows the dispersion of firm-level political risk tends to be higher during the 2008-9 recession (a regression of the residuals on the percentage growth in real GDP yields a negative and significant coefficient (-2.804, s.e.=1.670)). More striking, however, is the strong correlation with aggregate political risk: the dispersion in political risk across firms is high precisely when aggregate political risk is high. Regressing the residuals on the mean of $PRisk_{it}$ yields a coefficient of 0.790 (s.e.=0.056), implying a one-percentage-point increase in aggregate political risk is associated with a 0.79-percentage-point increase in the cross-sectional standard deviation of firm-level political risk.³⁸ As is already apparent from visual inspection, the latter association dominates: when we simultaneously regress the dispersion of firm-level political risk on GDP growth and aggregate political risk, the coefficient on the latter remains largely unchanged (0.875, s.e.=0.057), whereas the coefficient on the former flips sign (2.789,

³⁷We leave a careful quantification of these effects to future research. It requires resolving the issues of causality mentioned above, taking a systematic approach to identifying part of the variation in $PRisk_{it}$ that is inefficient (unnecessary), as well as a dynamic implementation of the decomposition in Hsieh and Klenow (2009).

³⁸This result (in combination with the findings shown in Table 4) is also consistent with the prediction in Pastor and Veronesi (2013) that stocks should be more volatile and correlated when (aggregate) political uncertainty is high.

s.e.=0.829). (See Appendix Table 16 for details and variations of these regressions.)

This strong association between aggregate political risk and the dispersion of firm-level political risk suggests politicians may to some extent control the dispersion of political risk across firms and that events that increase aggregate political risk may also transmit themselves through an increase in the firm-level dispersion of political risk. In this sense, part of the well-documented countercyclical variation in uncertainty (Bloom, 2009) may in fact have political origins.

The bottom panel of Figure 5 shows the distribution of firm-level political risk, without conditioning on a specific time-period. It further illustrates this variation is large relative to the variation in the whole panel (the standard deviation of this purely firm-level variation is 0.95 of the standard deviation of the full panel), and that it is positively skewed, with a fat right tail.

4.2 Case studies

As a useful illustration of the kind of firm-level political risk picked up by our measure, Figure 6 plots the time series of $PRisk_{it}$ for two particular firms: a large energy firm (panel A) and a small firm belonging to the information technology sector (panel B). For each spike in the time series, the figures provide a brief description of the risks associated with political topics discussed in the transcript.

As shown in panel A, a recurring theme in the genesis of the energy firm's $PRisk_{it}$ is risks associated with emission regulations. At various stages, EPA emissions rules are changed, challenged in court, withdrawn, and re-formulated, each time creating spikes in $PRisk_{it}$. When reading the underlying transcripts, it becomes clear why these regulatory actions have highly heterogeneous, firm-specific, impacts: Our example firm relies heavily on coal-burning furnaces of an older generation that specifically emit a lot of mercury and are also located such that they are subject to interstate emissions rules.³⁹ Other regulatory risks are also highly localized, where, for example, a regulator in Ohio considers changing rules on compensation for providing spare generating capacity, and an agency in North Carolina considers aggregation of electricity purchases. Both actions specifically impact our example firm because of its relatively large presence in these states. Altogether, only a small number of electricity generating firms might exhibit a similar exposure to these specific regulatory actions. Another recurring theme surrounds the likelihood of climate legislation and its interaction with health care reform. Although these kinds of legislations are arguably broad in their impact, here, too, we find a noticeable firm-specific element: the firm's executives are rooting for health care reform not because of its effect on the firm's health plan, but because it reduces the likelihood of Congress taking up climate legislation.

³⁹For an in-depth study of the heterogeneous effects of uncertainty about EPA interstate emissions rules, see Dorsey (2017).

The example firm in panel B is a smaller high-tech firm, specializing in voice-over-IP systems. As is evident from Figure 6, this firm’s exposure to political risk is much simpler, and centers almost entirely on government contracts. Specifically, the company hopes the government will make a strategic decision to invest in the firm’s (secure) voice-over-IP standard, and that in particular the Department of Defense will invest in upgrading its telephone infrastructure. Some of this uncertainty is again “aggregate” in the sense that it depends generally on the level of government spending, but much of it is also more specific to procurement decisions of individual agencies and the funding of specific government programs.

These case studies illustrate two main conclusions. First, $PRisk_{it}$ captures risks associated with a broad range of interactions between governments and firms, including regulation, litigation, legislation, budgeting, and procurement decisions. Second, given this breadth of government activities, the incidence of political risk could quite plausibly be highly volatile and heterogeneous across firms, such that much of the economically relevant variation of political risk is at the firm level.

5 Measuring Topic-Specific Political Risk

In the final step of our analysis we now demonstrate it is possible to generalize our approach in (1) to identify risks associated with specific political topics, rather than politics in general. To this end, we require a set of training libraries $\mathbb{Z} = \{\mathbb{P}_1, \dots, \mathbb{P}_Z\}$, each containing the complete set of bigrams occurring in one of Z texts archetypical of discussion of a particular political topic, such as health care policy or tax policy. As above, we then calculate the share of the conversation that centers on risks associated with political topic T as the weighted number of bigrams occurring in \mathbb{P}_T but not the non-political library, \mathbb{N} , that are used in conjunction with a discussion of political risk:

$$PRisk_{it}^T = \frac{\sum_b^{B_{it}} \left(1[b \in \mathbb{P}_T \setminus \mathbb{N}] \times 1[|b - p| < 10] \times \frac{f_{p,\mathbb{P}}}{B_{\mathbb{P}}} \times \frac{f_{b,\mathbb{P}_T}}{B_{\mathbb{P}_T}} \log(Z/f_{b,\mathbb{Z}}) \right)}{B_{it}}, \quad (6)$$

where p is the position of the nearest bigram already counted in our measure of overall political risk (1), that is, a political but not non-political bigram that is also near to a synonym for risk and uncertainty—the nearest bigram for which $1[b \in \mathbb{P} \setminus \mathbb{N}] \times 1[|b - r| < 10] > 0$. Both bigrams (p and b) are again weighted with their term frequencies and inverse document frequencies.

Because we must now distinguish between multiple political topics, b ’s inverse document frequency, $\log(Z/f_{b,\mathbb{Z}})$, now plays a more important role: it adjusts each bigram’s weighting for how unique its use is to the discussion of a specific topic compared to all the other political topics, where $f_{b,\mathbb{Z}}$ is the number of libraries in \mathbb{Z} that contain bigram b . For example, a bigram that occurs in all topic-based political

libraries is not useful for distinguishing a particular topic and is thus assigned a weight of $\log(Z/Z) = 0$. By contrast, this weight increases the more unique the use of this bigram is when discussing topic T , and is highest ($\log(Z/1)$) for a bigram that is used only in discussion of topic T but not in the discussion of any other topic.

To implement (6), we rely on the collection of newspaper articles, speeches, press releases, books, voting records, and bill sponsorships, compiled by ontheissues.org, which is a nonpartisan not-for-profit organization that uses this information to educate voters about the positions politicians take on key topics. We believe this source is particularly useful because it includes a wide variety of written texts as well as transcripts of spoken words. From the material provided on the website, we distilled training libraries for eight political topics: “economic policy & budget,” “environment,” “trade,” “institutions & political process,” “health care,” “security & defense,” “tax policy,” and “technology & infrastructure.”⁴⁰

Mirroring our approach in section 2, we begin by verifying that our topic-based measures correctly identify transcripts that feature significant discussions of risks associated with each of the eight political topics. We then examine firms’ lobbying activities and how they change in the face of political risk associated with each topic. The lobbying data are particularly attractive for this purpose, because we have information on the lobbying activities of each firm by political topic, allowing us to relate this information directly to our topic-specific measure of political risk. Finally, we use these data to study the impacts of three federal budget crises during the Obama presidency on political risk and lobbying.

5.1 Validation

Table 11 shows the top 15 bigrams most indicative of each of our eight political topics (the bigrams with the highest $\frac{f_{b,PT}}{B_{PT}} \log(Z/f_{b,Z})$). For example, the bigrams most associated with discussion of “economic policy & budget” include “balanced budget,” “legislation provides,” and “bankruptcy bill;” those most associated with “security & defense” include “on terror,” “from iraq,” and “nuclear weapons.” Looking across topics, these bigrams appear largely intuitive and provide an overview of the types of text classified by ontheissues.org under each topic heading. As before, the table also shows the text surrounding the highest-scoring bigrams within the three highest-scoring transcripts for each topic, which also give an impression as to each transcript’s content.

As before, we also read each of these transcripts in detail to verify our measure captures significant discussions of political risks associated with the expected topics, and found it does. For example, the transcript with the highest score in the “economic policy & budget” category discusses the possibility of government stimulus for the construction industry (Ashtead Group PLC in December 2008). Similarly,

⁴⁰ Appendix Table 17 gives details on the mapping between the materials provided on the website and these topics.

the transcript with the highest rank in the “security & defense” category (Circor International Inc in May 2011) features discussions of how government budget cuts and the winding down of activities in Iraq and Afghanistan affect the demand for the firm’s products.

Although our approach yields the expected results, we note a few minor exceptions. On four occasions, the conditioning on proximity to synonyms for risk again produces apparently false positives when considering only the text surrounding the highest-scoring bigrams shown in the table (the transcripts of Torchmark Corp., Exelon Corp., Radian Group Inc., and Magellan Health Services). However, a closer reading of these transcripts reveals the surrounding paragraphs do in fact contain significant discussions of political risks associated with the regulation of Medicare Part D plans, greenhouse gas emissions, housing finance reform, and health care reform, respectively.

We find only one one false positive among the 24 top transcripts listed in Table 11: the February 2007 transcript of a call by Faurecia, in the “economic policy & budget” category features no explicit discussion of political topics. The relatively high score on the transcript’s topic-based measure appears to be due to conference participants frequently using the bigram “the states” to refer to the situation in the United States, whereas the bigram is likely only political when used in reference to the 50 states in the US. With this one exception, our close reading confirms the topic-based measures correctly identify transcripts with significant discussions of risks associated with each of the eight political topics.

5.2 Lobbying by topic

The Center for Responsive Politics (CRP) reports for each firm-quarter total expenditure on lobbying and provides a list of topics these lobbying activities are directed toward. Using our mapping between the 80 topics given in the CRP dataset and our eight political topics (see Appendix Table 1), we generate a dummy variable that equals 1 if firm i lobbies on topic T in quarter t , and zero otherwise. Our main specification relating his lobbying activity to our topic-based measures of political risk takes the form:

$$\mathbb{1}[Lobbying_{i,t+1}^T > 0] * 100 = \delta_t + \delta_i + \delta_T + \theta PRisk_{it}^T + \gamma^T X_{it} + \epsilon_{it}^T, \quad (7)$$

where δ_t , δ_i , and δ_T represent time, firm, and topic fixed effects, respectively, and X_{it} always controls for the log of the firm’s assets and its political sentiment.⁴¹ The coefficient θ measures the association between the firm’s political risk associated with a given topic and its propensity to lobby on that topic.⁴²

Panel A of Table 12 shows estimates of θ , were column 3 corresponds directly to (7). The coefficient

⁴¹Because the lobbying data are semi-annual rather than quarterly before 2007, we drop the first and third quarters prior to 2007 from the sample and assign the outcome variable for the first half of the year to the second quarter and to the fourth quarter for the second half of the year.

⁴²We use a simple linear probability model instead of a Probit specification purely to facilitate interpretation.

of interest (0.794, s.e.=0.047) implies a one-standard-deviation increase in the political risk associated with a given political topic is associated with a 0.794-percentage-point increase in the probability that a given firm lobbies on that topic in the following quarter. Because on average only 7% of firms lobby on any given topic, this effect corresponds to an 11% increase relative to the mean. Column 5 shows our most demanding specification which also includes firm \times topic fixed effects, thereby only focusing on variation within firm and topic. Doing so reduces the coefficient of interest by an order of magnitude, although it remains statistically significant at the 1% level. Panel B reports similar findings using the log of one plus the dollar expenditure on lobbying as dependent variable, constructed under the assumption that firms spend an equal amount of funds on each topic they actively lobby on in a given quarter.

Our conclusion from this set of results is that the within-firm-and-topic variation of our topic-based measure has economic content, finding that firms actively manage political risk by lobbying on the political topics they are most concerned about.⁴³

5.3 Timing and causality

The granularity of these results, linking within-firm-and-topic variation in political risk to topic-specific lobbying expenditures in the subsequent quarter, warrants a brief consideration of the direction of causality. Two obstacles to attributing a causal interpretation to the coefficient θ remain.

The first challenge is that an unobserved non-political event simultaneously increases the share of the conversation devoted to risks associated with a particular political topic and, for reasons unrelated to this risk, increases the propensity to lobby on that same topic, but not other topics. Although thinking of examples of such an unobserved event is somewhat difficult, we cannot rule out this possibility. However, if such an omitted event indeed drives the identification of θ , we may expect it to affect lobbying expenditures before as much as after the discussion of the political topic at hand.

To probe this possibility, Appendix Table 18 replicates column 5 of Table 12—our most demanding specification relating lagged $PRisk_{it}^T$ to lobbying at $t + 1$ —while adding both contemporaneous and future $PRisk^T$ to the equation. The results show the coefficient on the lag is almost unchanged (0.081, s.e.=0.030), and it shows a larger effect than both the contemporaneous $PRisk_{i,t+1}^T$ (0.064, s.e.=0.030) and the lead (0.048, s.e.=0.031), which is statistically indistinguishable from zero. If anything, the lag thus dominates the lead, consistent with a causal interpretation of the results. We interpret this result, however, with caution given the relatively low frequency of the data, the high persistence of lobbying activities,⁴⁴ and the fact that the three point estimates are not dramatically different from each other.

⁴³ Going one step further, Appendix Figure 5 probes the heterogeneity of this effect across topics by allowing the coefficient θ in (7) to vary by topic.

⁴⁴A pooled regression of $Lobbying_{i,t+1}(\mathbb{1} * 100)$ on $Lobbying_{i,t}(\mathbb{1} * 100)$ gives a coefficient of 0.877 (s.e.=0.056). Firms that

The second challenge to a causal interpretation is that a politically engaged firm may lobby the government on a given topic—regardless of the risks associated with the issue—and then have to defend financial or other risks resulting from this lobbying activity during a conference call, or it might lobby in anticipation of future innovations to political risk. Again, the timing of the effect weighs somewhat against this interpretation, but we cannot exclude it in the absence of a natural experiment.

This narrow issue of identification aside, a deeper challenge results from the fact that not all political risk is generated by the political system itself, but rather arises in reaction to external forces. For example, an acute liquidity crisis in financial markets may prompt regulators to act, thus creating political risk from the perspective of the firm. In this case, the political risk itself results from politicians’ attempts to minimize adverse impacts from the crisis. In other words, a meaningful distinction exists between political risk that fundamentally originates from the political system and political risk that arises due to other forces. Again, disentangling the causal effects of these different types of political risks would require a natural experiment.

Although we have no such natural experiments available, we can nevertheless speak to this issue by making use of three historical episodes that allow us to trace rises in political risk directly to specific political crises. We discuss these cases in the next section.

5.4 Case studies

During the Obama presidency, the federal government suffered a sequence of budget crises surrounding the so-called “debt ceiling,” the “fiscal cliff,” and the “shutdown” of the federal government. These episodes are of special interest because they arguably created uncertainty about the federal government’s ability to service its debts and its future borrowing capacity that resulted purely from the inability of politicians to reach a compromise in a timely fashion, and not from some other unobserved factor. Moreover, each of these episodes is associated with a unique bigram that comes into use in conference-call transcripts only during the period of interest and not before. These unique bigrams allow us to measure which firms appeared most concerned with the turmoil associated with these episodes.

The federal debt ceiling was reached on May 16, 2011. By August 2, 2011, Secretary Geithner stated that the treasury’s “extraordinary measures” for providing operating funds had been exhausted. An imminent default on federal debt was averted only by a last-minute budget deal. As shown in Figure 7, the use of the bigram “debt ceiling” in conference calls peaks around that time (in 2011 q3). In December 2012, the expiration of the Bush-era tax cuts and a scheduled reduction in government

begin lobbying thus tend to continue doing so for several quarters. Lobbying by topic exhibits similarly high persistence (0.882, s.e.=0.005).

spending (“sequestration”) threatened to send America hurtling over the “fiscal cliff.” In addition, on December 31, 2012, the debt ceiling was also expected to be reached. Together, these events led to the debt-ceiling crisis of 2013. As shown in Figure 7, the occurrence of the bigrams “fiscal cliff” and “debt ceiling” peaks in q4 2012 to q1 2013, albeit the latter lower than in q3 2011. Finally, on October 1, 2013, congress failed to reach agreement on a measure to avoid a partial government shutdown. The shutdown lasted for 16 days, before a compromise was reached. Figure 7 shows the use of the bigram “government shutdown” peaks sharply around q4 2013. Notably, the figure further shows each of these episodes is associated with a marked increase in the average across firms in our measure of political risk associated with “economic policy & budget,” $PRisk_{it}^{ep\&b}$.

Table 13 probes this apparent effect of the three budget crises on $PRisk_{it}^{ep\&b}$ by examining the cross section of firms. Columns 1-3 in Panel A report that firms that use the bigrams “debt ceiling,” “fiscal cliff,” and “government shutdown” more frequently in their earnings calls held during these respective periods tend to experience a significantly higher increase in $PRisk_{it}^{ep\&b}$ relative to the previous quarter.

Although we have no quasi-experimental variation in the identities of the firms most affected by these episodes, we can show the firms using the three bigrams more frequently tend to rely on the federal government for significantly larger shares of their revenues.⁴⁵ Moreover, this approach arguably enables us to isolate variation in political risk induced by the political process itself, namely, the inability of decision makers to arrive at compromises in a timely fashion.

How might firms react to this politically-induced increase in risk associated with the federal budget? To answer this question, Panel B of Table 13 reports estimates of a regression of a dummy variable that equals 1 if a firm lobbies on the topic “economic policy & budget” in a given quarter on a full set of time and firm fixed effects, and the number of times a conference call contains any of the three bigrams associated with the three crises. We find one additional mention of one of the three bigrams is associated with a 0.698-percentage-point increase (s.e.=0.299) in the probability that the firm lobbies the federal government on the topic of “economic policy & budget” in the following quarter.⁴⁶

In column 2, we regress the dummy for lobbying on this specific topic on $PRisk_{it}^{ep\&b}$, returning a positive and significant coefficient (0.183, s.e.=0.084). Finally, in column 3, we use polynomials of the number of mentions of “debt ceiling,” “fiscal cliff,” and “government shutdown” during the three respective periods as instruments for $PRisk_{it}^{ep\&b}$. The result suggests a one-standard-deviation increase in political risk associated with “economic policy & budget” attributable to the three budget crises is associated with a 2.430-percentage-point increase (s.e.=0.937) in the probability that a given firm

⁴⁵A pooled OLS regression of # of “debt ceiling,” “fiscal cliff,” and “government shutdown” on a firm’s share in revenue from government contracts (using all firms and quarters) yields a coefficient of 0.154 (s.e.=0.059, clustered by firm).

⁴⁶In total, 2,160 firm-quarters show use of one of these bigrams (on average used 1.69 times).

lobbies on that topic. Under the assumption that firms spend the same dollar amount on each topic they lobby on, this finding translates to a 30.3% (s.e.=10.6%) increase in dollars spent on lobbying on “economic policy & budget” (column 4).

We cautiously interpret these coefficients as the local average treatment effect of the Obama-presidency budget crises on the probability that firms most concerned with these crises lobby the federal government on the topic of “economic policy & budget” in the subsequent quarter.

The notable increase in the coefficient between the OLS and IV specifications (by a factor of 14) is consistent with the view that political risks attributable to the political process itself may be more amenable to influencing by lobbying than political risks resulting from some external force. Alternatively, the increase may also be explained by the presence of substantial measurement error or some other force contributing to endogenous selection.

6 Conclusion

Political decisions on regulation, taxation, expenditure, and the enforcement of rules have a major impact on the business environment. Even in well-functioning democracies, the outcomes of these decisions are often hard to predict, generating risk, as witnessed, for example, by the recent episodes surrounding the shutdown of the US federal government or the ongoing debate about health care reform. A major concern among economists is that the effects of such political risk on the decisions of households and firms might entail social costs that may outweigh potential upsides even of well-meaning reforms, prompting questions about the social costs of the fits and starts of political decision-making. However, quantifying the effects of political risk associated with specific political decisions has often proven difficult, partially due to a lack of measurement.

In this paper, we adapt simple tools from computational linguistics to construct a new measure of political risk faced by individual firms: the share of their quarterly earnings conference calls that they devote to political risks. This measure allows us to quantify, and decompose by topic, the extent of political risk faced by individual firms over time.

We show a range of results corroborating our interpretation that our measure indeed reflects meaningful firm-level variation in exposure to political risk: we find that it correctly identifies conference calls that center on risks associated with politics, that aggregations of our measure correlate strongly with measures of aggregate and sectoral political risk used in the prior literature, and that it correlates with stock market volatility and firm actions — such as hiring, investment, lobbying, and donations to politicians — in a way that is highly indicative of political risk.

Using this measure, we document that a surprisingly large share of the variation in political risk appears to play out at the level of the firm, rather than the level of the sector or the economy as a whole. About two-thirds of the variation of our measure is accounted for changes in the assignment of political risk across firms within a given sector. Although part of this variation is likely measured with error, we find it has economic content, in the sense that it is significantly associated with all the same firm-level outcomes and actions outlined above.

An immediate implication of these results is that the economic impact of political risk is not well described by conventional models in which individual firms have relatively stable exposures to aggregate political risk. Instead, political shocks appear to be a significant source of firm-level (idiosyncratic) risk, and firms may well be as concerned about their relative position in the distribution of firm-level political risk as they are about aggregate political risk. Consistent with this interpretation, we find the distribution of firm-level political risk has high variance and a fat right tail.

Our main conclusion from this set of results is that the effectiveness of political decision-making may affect the economy, not only by affecting aggregate political risk (as is the focus of much of the existing literature), but also by creating idiosyncratic political risk. Such idiosyncratic political risk may affect the macroeconomy through three distinct channels. First, it may lower total factor productivity by distorting the allocation of resources across firms within sector. Second, it may prompt socially wasteful diversion of resources toward lobbying and other attempts to actively manage firm-level political risk. Third, a recent literature in macroeconomics has argued that idiosyncratic risk, regardless of its origin, may have independent effects on the level of hiring and investment in a variety of settings.

Consistent with the view that politicians have some control over the level of idiosyncratic political risk, we also find that the dispersion of firm-level political risk co-moves strongly with aggregate political risk, rising when aggregate political risk is high. Because aggregate political risk tends to be high in economic downturns, this association may also explain part of the countercyclical nature of idiosyncratic risk (both political and non-political), which is the subject of a broader literature.

In addition to our measure of overall political risk, we also generate additional measures of overall risk, non-political risk, corresponding measures of political, and non-political sentiment, as well as additional measures of political risks associated with eight specific political topics. Using these topic-specific measures, we show that firms that devote more time to discussing risks associated with a given political topic in a given quarter are more likely to begin lobbying on that topic in the following quarter.

Our results leave a number of avenues for future research. In particular, we hope the ability to measure firm-level variation in political risk will contribute to identifying and quantifying causal effects of political risk in future work, for example, by combining our data with information about natural

experiments affecting the degree of political risk associated with particular topics. One such avenue might be to apply our methodology to UK and EU-based firms to study how political risk triggered by Brexit affects firm behavior.

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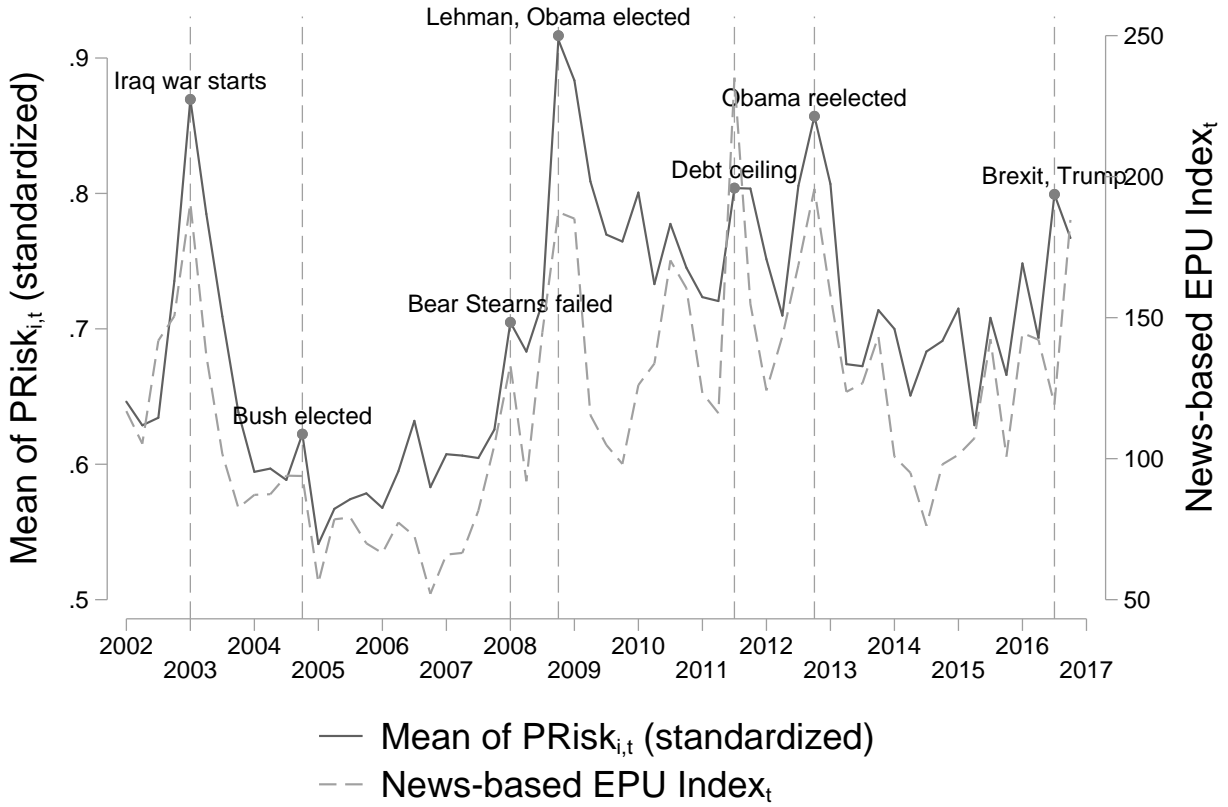
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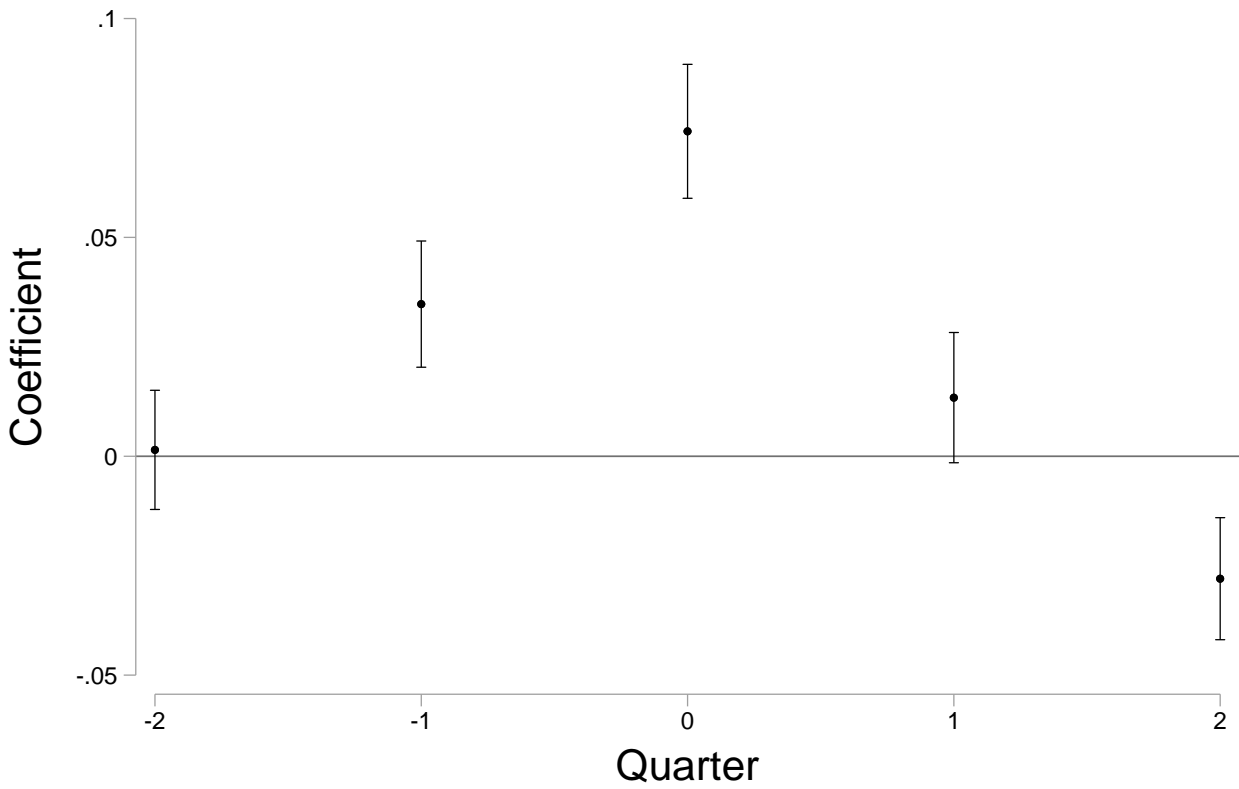
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Figure 1: Variation in $PRisk_{i,t}$ over time and correlation with EPU



Notes: This figure shows the time-average of $PRisk_{i,t}$ (standardized) across firms in each quarter together with the news-based Economic Policy Uncertainty Index developed by Baker, Bloom, and Davis (2016). The Pearson correlation between the two series is 0.821 with a p-value of 0.000. $PRisk_{i,t}$ is standardized by its standard deviation in the panel. The Pearson correlation between the time-average of $PRisk$ with the CBOE Volatility Index (VIX) is 0.608 with a p-value of 0.000. $PRisk_{i,t}$ is standardized by its standard deviation in the panel.

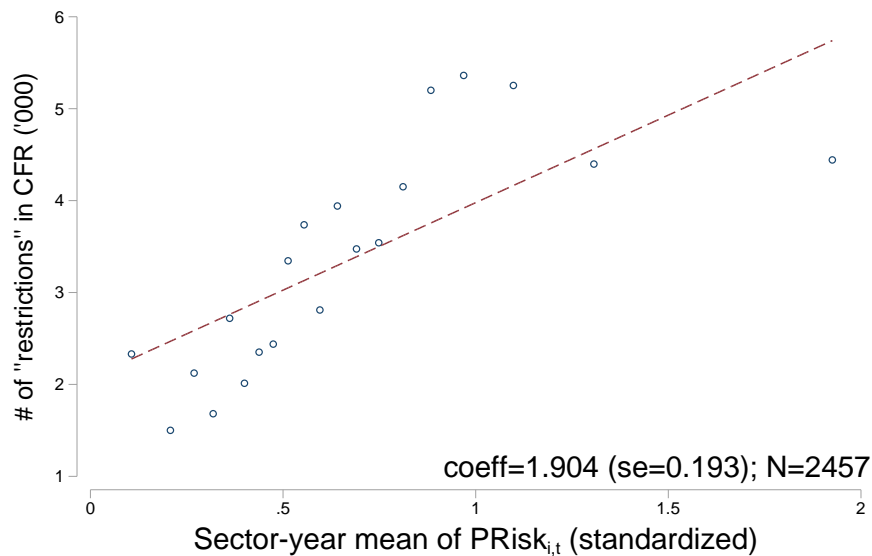
Figure 2: Variation in $PRisk_{i,t}$ around federal elections



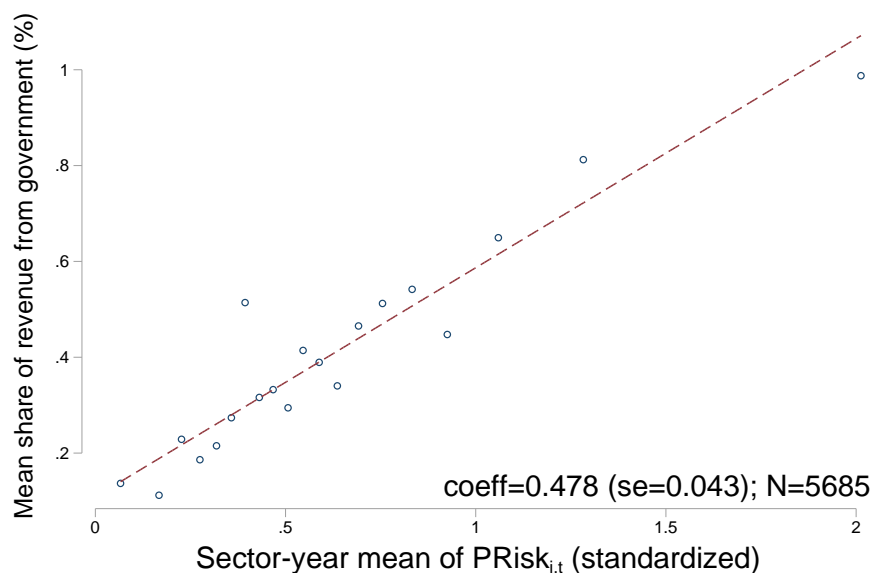
Notes: This figure plots the coefficients and 95% confidence intervals from a regression of $PRisk_{i,t}$ (standardized) on dummy variables indicating quarters with federal (i.e., presidential and congressional) elections, as well as two leads and lags. The specification also controls for firm fixed effects and the log of firm assets. $PRisk_{i,t}$ is standardized by its standard deviation. Standard errors are clustered at the firm level.

Figure 3: $PRisk_{i,t}$ and sector-level measures of proxies to politics

Panel A: Index of regulatory constraints

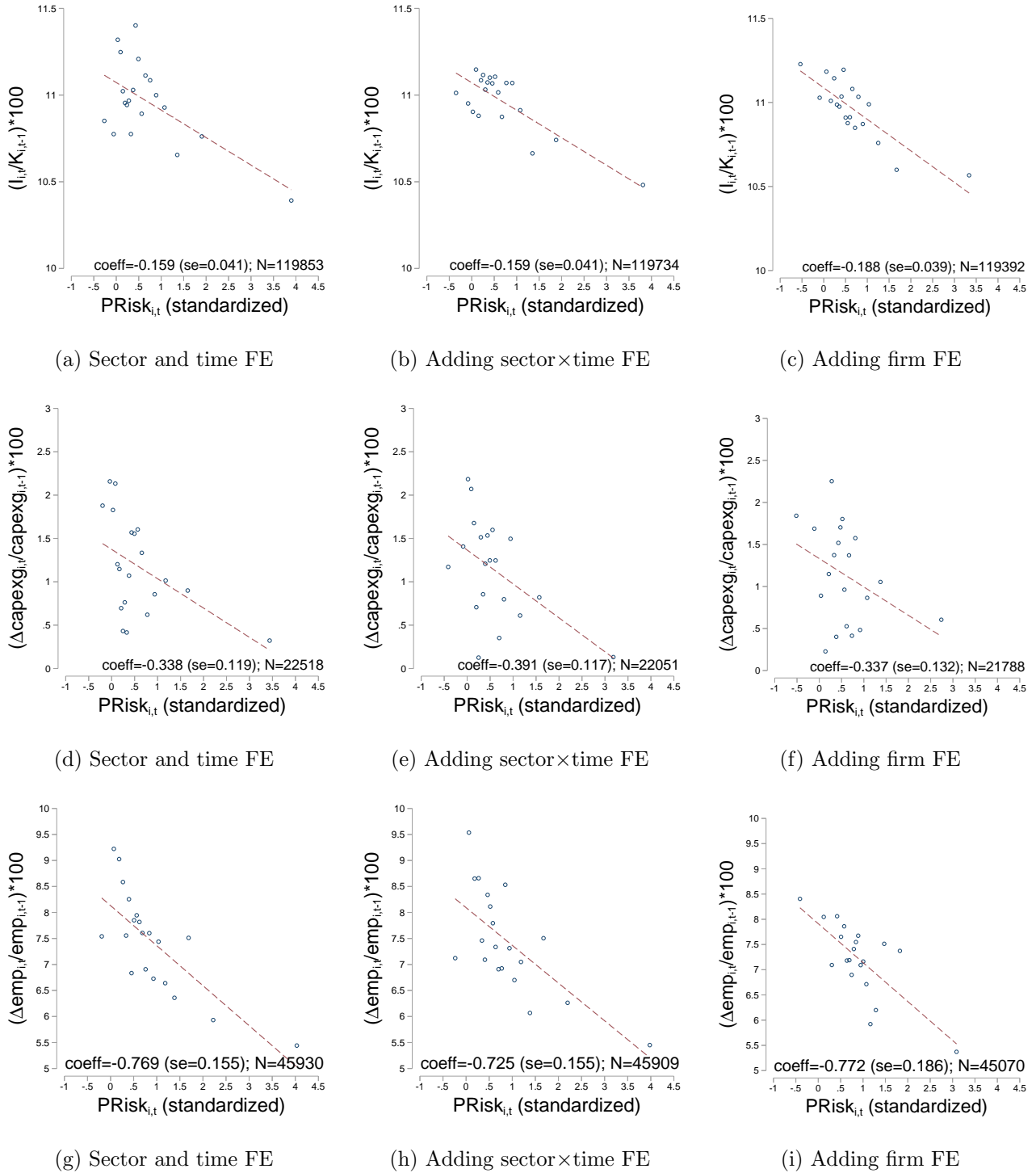


Panel B: Share of revenue from federal government



Notes: This figure shows binned scatterplots of the relationship between the sector-year average of $PRisk_{i,t}$ (standardized) and two different measures of sector exposure to politics. In Panels A and B the number of industries is 211 and 413, respectively. In Panel A, the index of regulatory constraints is calculated as the sum for each sector-year pair of the probability that a part of the Code of Federal Regulations is about that sector multiplied by the number of occurrences of restrictive words – “shall,” “must,” “may not,” “prohibited,” and “required” in that part. For more details, see Al-Ubaydli and McLaughlin (2015). In Panel B, the outcome variable is the sector-year average of firms’ share of revenue that comes from the federal government. Firm i ’s share of revenue from the federal government is $federal\ contracts_{i,t}$ (as measured in Table 10) divided by total net sales. $PRisk_{i,t}$ is standardized by its standard deviation.

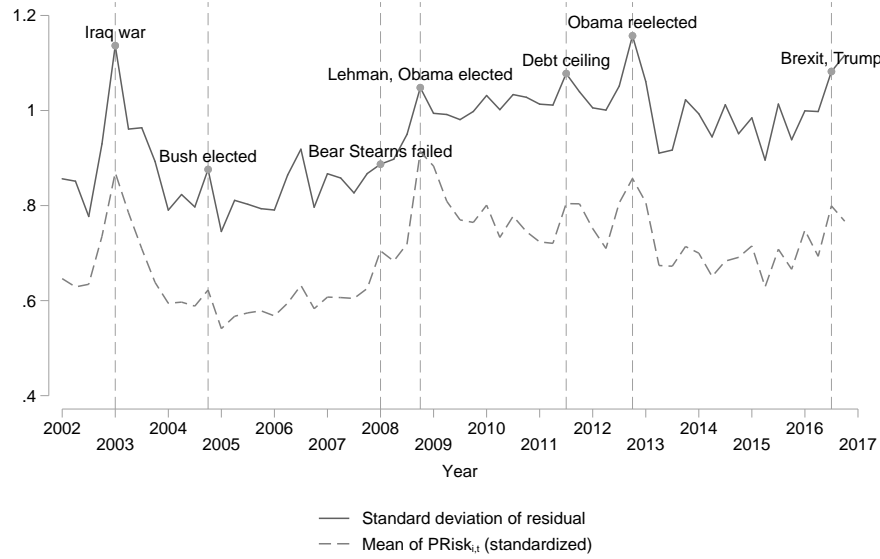
Figure 4: Associations between $PRisk_{i,t}$ and corporate actions



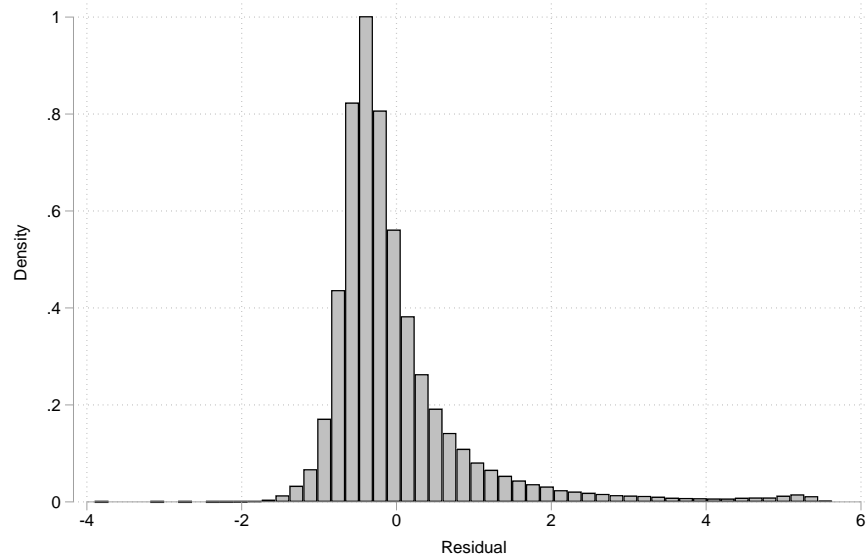
Notes: This figure shows nine panels of binned added-variable plots for $PRisk_{i,t}$ (standardized). Going from top to bottom, the panels are for investment, $I_{i,t}/K_{i,t-1} * 100$, Panels a, b, and c), capex guidance, $\Delta capex_{i,t} / capex_{i,t-1} * 100$, (Panels d, e, and f), and employment, $\Delta emp_{i,t} / emp_{i,t-1} * 100$, (Panels g, h, and i). The left-hand panels control for sector and time, the middle panels control, in addition, for sector \times time interactions, and the right-hand panels control, in addition, for firm fixed effects (thus controlling simultaneously for time, sector, firm and sector \times time fixed effects). All specifications control for the log of firm assets. $PRisk_{i,t}$ is standardized by its standard deviation.

Figure 5: Dispersion of firm-level political risk

(a) Panel A: Time-series variation in the cross-sectional standard deviation of $PRisk_{i,t}$



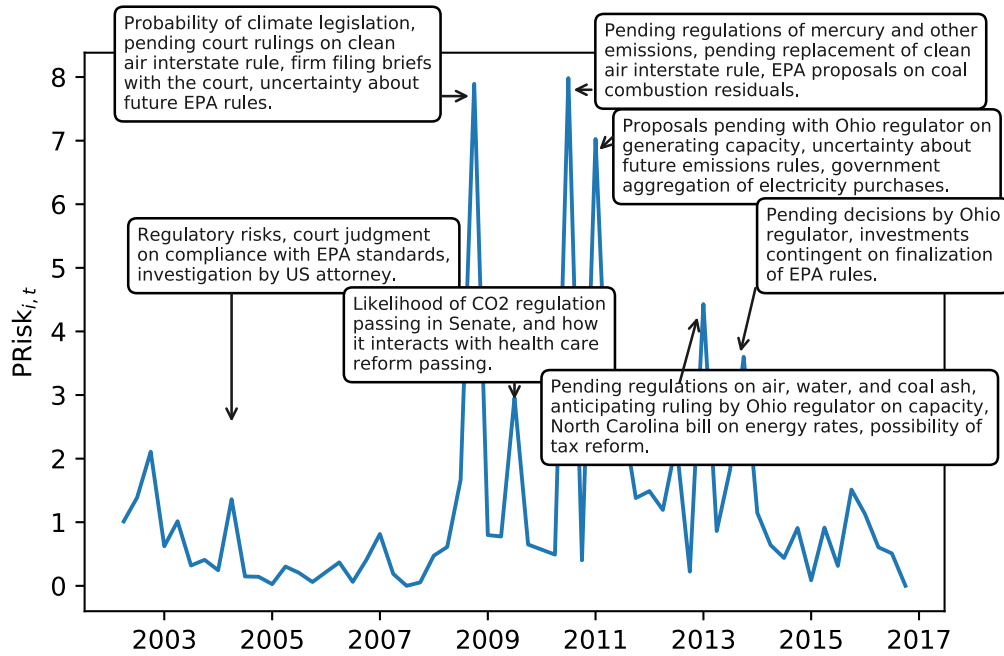
(b) Panel B: Distribution of $PRisk_{i,t}$



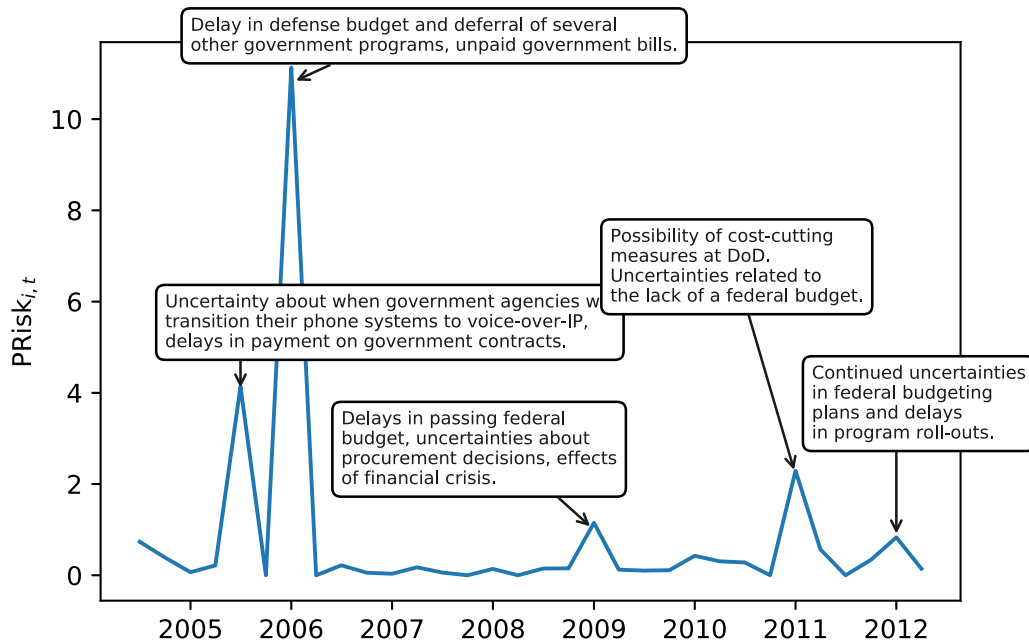
Notes: Panel A plots the mean of $PRisk_{i,t}$ (standardized) and the cross-sectional standard deviation at each point in time of the residual from a projection of $PRisk_{i,t}$ (standardized) on sector fixed effects, time fixed effects, and the interaction of time and SIC2-digit sector fixed effects. A regression of the former on the latter yields a coefficient of .989 (s.e. = .0672). $PRisk_{i,t}$ is standardized by its standard deviation in the panel. Panel B shows a histogram of the residuals from the above-mentioned projection. The standard deviation of the distribution is .959; the skewness is 2.797.

Figure 6: Case studies

(a) Panel A: $PRisk_{i,t}$ of large energy firm

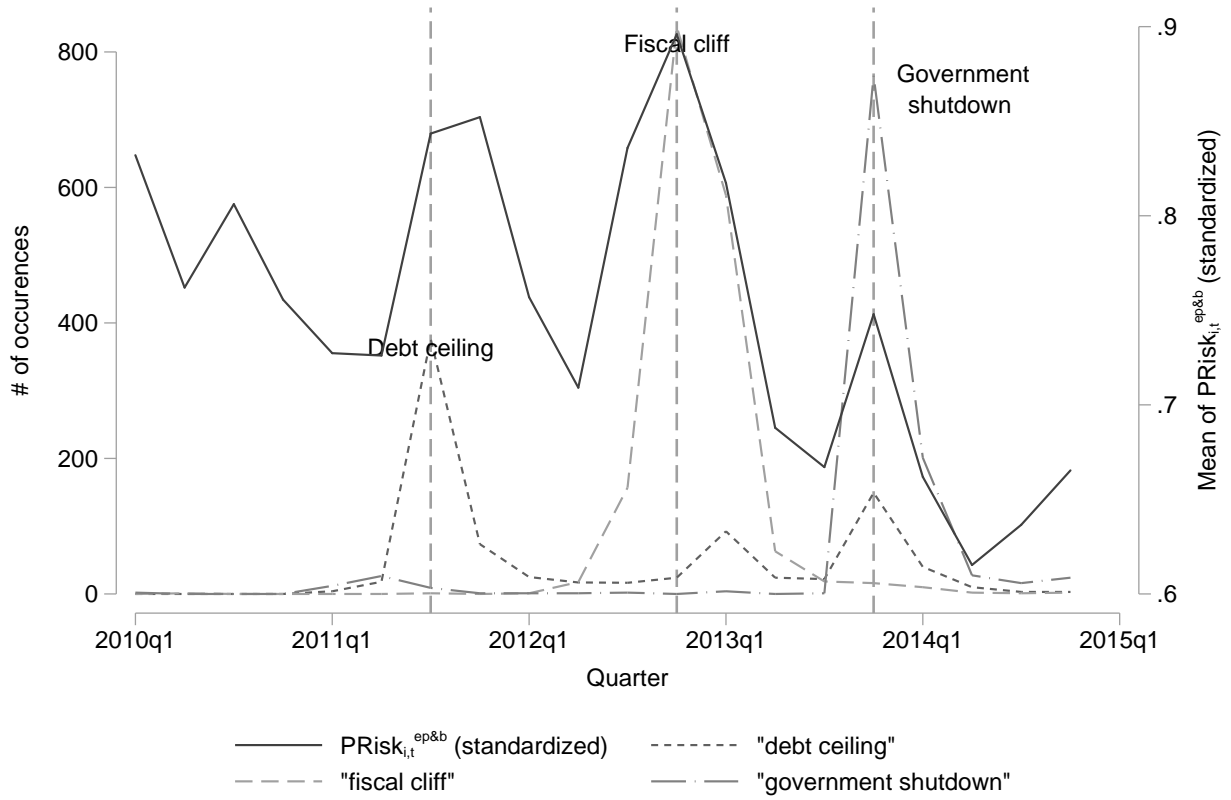


(b) Panel B: $PRisk_{i,t}$ of small information technology firm



Notes: This figure shows $PRisk_{i,t}$ (standardized) for two illustrative firms. The first (Panel A), shows $PRisk_{i,t}$ of an energy generation company heavily invested in coal-burning furnaces of an older generation. The second (Panel B), shows $PRisk_{i,t}$ of a small information technology firm specializing in secure voice-over-IP communications systems. The bubbles in each figure give a summary of the political risks discussed in each transcript.

Figure 7: Case studies: Debt ceiling, fiscal cliff, and government shutdown



Notes: This figure plots the total number of occurrences of the terms “debt ceiling”, “fiscal cliff”, and “government shutdown” across all transcripts within a given quarter together with the average across firms of our measure of political risk associated with “economic policy & budget”, $PRisk_{i,t}^{ep\&b}$. $PRisk_{i,t}^{ep\&b}$ is standardized by its standard deviation in the panel.

Table 1: Summary statistics

PANEL A: FIRM-QUARTER	Mean	Median	St. Dev.	Min	Max	N
PRisk _{<i>i,t</i>} (standardized)	0.70	0.37	1.00	0.00	6.08	176,173
PSentiment _{<i>i,t</i>} (standardized)	0.90	0.85	1.00	-2.13	3.96	176,173
Assets _{<i>i,t</i>} (millions)	15,271	1,217	97,502	0.13	3,069,706	173,887
Realized volatility _{<i>i,t</i>} (standardized)	1.52	1.27	1.00	0.21	8.31	162,153
Implied volatility _{<i>i,t</i>} (standardized)	2.05	1.82	1.00	0.46	6.31	115,059
Earnings announcement surprise _{<i>i,t</i>}	-0.01	0.00	1.43	-235.83	301.81	161,403
Stock return 7 days prior to earnings call _{<i>i,t</i>}	0.00	0.00	0.02	-0.24	0.40	148,196
Investment rate, $I_{i,t}/K_{i,t-1}$	0.11	0.09	0.11	-0.03	1.07	119,853
Δ capex guidance _{<i>i,t</i>} /capex guidance _{<i>i,t-1</i>}	0.01	0.00	0.16	-0.44	0.87	22,520
Δ sales _{<i>i,t</i>} /sales _{<i>i,t-1</i>}	0.05	0.02	0.35	-0.98	3.46	173,887
Lobby expense _{<i>i,t</i>} (thousands)	80.08	0.00	381.08	0.00	15,460.00	147,228
Donation expense _{<i>i,t</i>} (thousands)	5.13	0.00	27.71	0.00	924.50	176,173
# of recipients _{<i>i,t</i>}	2.73	0.00	14.01	0.00	521.00	176,173
Hedge _{<i>i,t</i>}	0.06	0.00	0.24	0.00	1.00	176,173
Federal contracts _{<i>i,t</i>} (thousands)	3,516	0.00	49,488	0.00	3,841,392	162,124
PRisk Economic Policy & Budget _{<i>i,t</i>} (standardized)	0.48	0.22	1.00	0.00	64.75	176,173
PRisk Environment _{<i>i,t</i>} (standardized)	0.33	0.13	1.00	0.00	88.78	176,173
PRisk Trade _{<i>i,t</i>}	0.30	0.10	1.00	0.00	164.55	176,173
PRisk Institutions & Political Process _{<i>i,t</i>} (standardized)	0.39	0.16	1.00	0.00	71.69	176,173
PRisk Health _{<i>i,t</i>} (standardized)	0.27	0.10	1.00	0.00	73.02	176,173
PRisk Security & Defense _{<i>i,t</i>} (standardized)	0.42	0.19	1.00	0.00	123.42	176,173
PRisk Tax Policy _{<i>i,t</i>}	0.37	0.15	1.00	0.00	97.37	176,173
PRisk Technology & Infrastructure _{<i>i,t</i>} (standardized)	0.41	0.17	1.00	0.00	66.67	176,173
PANEL B: FIRM-YEAR	Mean	Median	St. Dev.	Min	Max	N
PRisk _{<i>i,t</i>} (standardized)	0.90	0.59	1.00	0.00	5.97	48,679
PSentiment _{<i>i,t</i>} (standardized)	1.09	1.05	1.00	-1.90	4.07	48,679
Δ emp _{<i>i,t</i>} /emp _{<i>i,t-1</i>}	0.07	0.03	0.30	-0.78	2.50	45,930
PANEL C: FIRM-TOPIC-QUARTER	Mean	Median	St. Dev.	Min	Max	N
PRisk _{<i>i,t</i>} ^{<i>T</i>} (standardized)	0.61	0.27	1.00	0.00	6.34	1,177,824
Lobby _{<i>i,t</i>} ^{<i>T</i>} (1)	0.07	0.00	0.25	0.00	1.00	1,177,824

Notes: This table shows the mean, median, standard deviation, minimum, maximum, and number of non-missing observations of all variables that are used in the subsequent regression analyses. Panels A, B, and C show the relevant statistics for the regression sample at the firm-year, firm-quarter, and firm-topic-quarter unit of analysis, respectively. In Panel A, $PRisk_{i,t}$ is the average for a given firm and quarter of the transcript-based scores of political risk; in Panel B, it is the average for a given firm and year; and in Panel C, $PRisk_{i,t}^T$ is the average for a given firm and quarter of the transcript-based scores of topic T . Each of the three are capped at the 99th percentile and standardized by their respective standard deviation. $PSentiment_{i,t}$ is capped at the 1st and 99th percentile and standardized by its standard deviation. Realized volatility_{*i,t*} is the standard deviation of 90-day stock holding returns of firm i in quarter t . Implied volatility_{*i,t*} is for 90-day at-the-money options of firm i and time t . Both realized and implied volatility are winsorized as in Stein and Stone (2013). Stock return 7 days prior to earnings call_{*i,t*} is the average stock return for the 7 days prior to the earnings call at date t . Earnings announcement surprise_{*i,t*} is defined as $(EPS_{i,t} - EPS_{i,t-4})/price_{i,t}$, where $EPS_{i,t}$ are earnings per share (basic) of firm i at time t and $price_{i,t}$ is the closing price of quarter t . Capital investment, $I_{i,t}/K_{i,t-1}$, is a measure for capital expenditure, and is calculated recursively using a perpetual-inventory method and winsorized as in Stein and Stone (2013). Capex guidance, $\Delta capex_{i,t}/capex_{i,t-1}$, is the quarter-to-quarter percentage change of the capital expenditure guidance about the closest (usually current) fiscal year-end. We allow for a quarter gap if no guidance (about the same fiscal year-end) was given in the preceding quarter and winsorize the resulting variable at the 1st and 99th percentile. Net sales, $\Delta sales_{i,t}/sales_{i,t-1}$ is the change in quarter-to-quarter sales over last quarter's value, winsorized at the 1st and 99th percentile. Lobby expense_{*i,t*} is the total lobby expense during quarter t by firm i . Donation expense_{*i,t*} the sum of all contributions paid to federal candidates in quarter t by firm i . # of recipients_{*i,t*} is defined as the total number of recipients of donations made in quarter t by firm i . Hedge_{*i,t*} is a dummy variable equal to one if donations to Republicans over donations to Democrats are between the 25th and 75th percentile of the sample. Federal contracts_{*i,t*} is the net value from all federal contracts (excluding modifications) of firm i in quarter t . Net hiring, $\Delta emp_{i,t}/emp_{i,t-1}$, is the change in year-to-year employment over last year's value and is winsorized at the 1st and 99th percentile. Finally, $PRisk_{i,t}^T$ where $T = \{\text{Economic policy \& budget, Environment, Trade, Institutions \& political process, Health, Security \& defense, Tax policy, Technology \& infrastructure}\}$, are the separate topic scores, capped at the 99th percentile and standardized by their respective standard deviation. All variables are restricted to the set of observations of the largest regression sample that is reported in any of the subsequent tables.

Table 2: Top 120 political bigrams used in construction of $PRisk_{i,t}$

Bigram	$(f_{b,\mathbb{P}}/B_{\mathbb{P}}) \times 10^5$	Frequency	Bigram	$(f_{b,\mathbb{P}}/B_{\mathbb{P}}) \times 10^5$	Frequency
the constitution	201.15	9	governor and	26.79	11
the states	134.29	203	government the	26.39	56
public opinion	119.05	4	this election	25.98	26
interest groups	118.46	8	political party	25.80	5
of government	115.53	316	american political	25.80	2
the gop	102.22	1	politics of	25.80	5
in congress	78.00	107	white house	25.80	21
national government	68.03	7	the politics	25.80	31
social policy	62.16	1	general election	25.22	30
the civil	60.99	64	and political	25.22	985
elected officials	60.40	3	policy is	25.22	135
politics is	53.95	7	the islamic	25.04	1
political parties	51.61	3	federal reserve	24.63	119
office of	51.02	58	judicial review	24.04	6
the political	51.02	1091	vote for	23.46	6
interest group	48.09	1	limits on	23.46	53
the bureaucracy	48.09	1	the faa	23.28	22
and senate	46.33	19	the presidency	22.87	2
government and	44.57	325	shall not	22.87	4
for governor	41.48	2	the nation	22.87	52
executive branch	40.46	3	constitution and	22.87	3
support for	39.88	147	senate and	22.87	28
the epa	39.15	139	the va	22.65	77
in government	38.70	209	of citizens	22.28	12
congress to	36.95	19	any state	22.28	7
political process	36.36	18	the electoral	22.28	5
care reform	35.77	106	a president	21.70	6
government in	35.19	77	the governments	21.70	201
due process	35.19	6	clause of	21.11	1
president obama	34.60	7	and congress	21.11	7
and social	34.60	140	the partys	21.11	1
first amendment	34.01	1	the taliban	20.64	1
congress the	34.01	9	a yes	20.64	12
the republican	33.43	10	other nations	20.53	1
tea party	33.43	1	passed by	20.53	13
the legislative	33.43	92	states or	20.53	40
of civil	32.84	14	free market	20.53	29
court has	32.84	30	that congress	20.53	30
groups and	32.25	109	national and	20.53	194
struck down	31.67	3	most americans	19.94	2
shall have	31.67	7	of religion	19.94	1
civil war	31.67	8	powers and	19.94	3
the congress	31.67	50	a government	19.94	92
the constitutional	29.91	9	politics and	19.94	22
ruled that	29.32	15	the south	19.94	406
the presidential	29.32	121	government is	19.94	235
of representatives	28.74	10	yes vote	19.39	1
policy goals	28.15	2	to enact	19.35	6
african americans	28.15	2	political system	19.35	6
economic policy	28.15	15	proposed by	19.35	25
of social	28.15	31	the legislature	19.35	32
a political	28.15	121	the campaign	19.35	41
of speech	27.56	1	federal bureaucracy	18.77	3
civil service	27.56	2	and party	18.77	2
government policy	27.56	52	governor in	18.76	1
federal courts	27.56	1	state the	18.26	35
argued that	26.98	8	executive privilege	18.18	1
the democratic	26.98	7	of politics	18.18	4
islamic state	26.92	1	the candidates	18.18	11
president has	26.86	7	national security	18.18	59

Notes: This table shows the top 120 bigrams with the highest term frequency ($f_{b,\mathbb{P}}/B_{\mathbb{P}}$) and receiving the highest weight in the construction of $PRisk_{i,t}$. The frequency counts the number of occurrences of the bigram across all transcripts.

Table 3: Transcript excerpts with highest $PRisk_{i,t}$: Panel A

Firm name	Call date	$PRisk_{i,t}$ (standardized)	Discussion of political risks associated with:	Text surrounding bigram with highest weight ($f_{b,p}/B_p$)
NEVADA GOLD CASI-NOS INC	10-Sep-2008	72.45	<ul style="list-style-type: none"> - impact of statewide smoking ban on revenues; - ballot initiative to amend the constitution to remove caps on bets; - EPA determinations concerning project development. 	gaming industry is currently supporting a ballot initiative to amend the constitution to authorize an increase in the —BET— limits allow additional
Axis Capital Holdings Limited	9-Feb-2010	67.93	<ul style="list-style-type: none"> - Portugal, Greece, Ukraine, and Kazakhstan. - developments regarding USAID, a major customer; - FDA approval of company products; - Senate vote on stimulus funding and government funding of AIDS/HIV prevention; - restrictions on funding of organizations that permit abortion. 	about the political —RISK— business particularly really shouldnt be looked at on a market acceptance the economic and business environment and the impact of government pressures currency — RISKS— capacity efficiency and supply constraints and other
Female Health	10-Feb-2009	61.61	<ul style="list-style-type: none"> - passage of California Senate Bill on workers's compensation. 	of —HAZARD— groups but as you start moving it around the states you can have an impact robert paun sidoti company analyst
Employers Holdings Inc	01-May-2014	61.11	<ul style="list-style-type: none"> - state and Federal budgets; - Federal stimulus package; - funding of Medicaid. 	governments both president obamas budget proposal and separate legislation —PENDING— in congress would provide funding to continue the medicaid stimulus for another
National Mentor Holdings, Inc.	12-Feb-2010	59.35	<ul style="list-style-type: none"> - collaboration with Pentagon to develop technology to counter IED/roadside bombs; - funding of weapons programs. 	magnitude of government funding and customer orders dependence on sales to government customers
Applied Energetics, Inc.	11-May-2009	57.36	<ul style="list-style-type: none"> - impact of revenues of government cost cutting initiatives. 	sure benoit poirier desjardins securities analyst okay and in terms of government cost cutting initiatives is there any —RISK— of missing consensus
Calian Group Ltd	09-Feb-2011	57.26	<ul style="list-style-type: none"> - Australian election for prime minister; - likelihood of carbon tax introduction. 	leadership i just wondered if you had concerns about how the political —INSTABILITY— might affect policies that have ramifications for the industry
Insurance Group Ltd	23-Feb-2012	53.98	<ul style="list-style-type: none"> - impact of the composition of Congress on the likelihood of tort reform; - Florida state politics. 	the constitution of congress changing in such a way after this election
FPIC Insurance Group, Inc.	30-Oct-2008	53.98	<ul style="list-style-type: none"> - TARP and CPP programs; - developments in Freddie Mac; - consequences of a change in administration and party in power. 	a —CHANCE— for national tort reform and i dont see was an accurate metaphor and really given all the — UNCERTAINTIES— of government involvement in operations and business activities and given the capital
BANKFINANCIAL CORP	4-Nov-2008	53.47		

Notes: This panel lists the top 10 transcripts sorted on $PRisk_{i,t}$ together with their associated firm name, earnings call date, $PRisk_{i,t}$ (standardized), a summary of relevant discussions of political risks in the transcript, and the text surrounding the bigram that has received the highest weight in the transcript. Bigrams for which $b \in \mathbb{P} \setminus \mathbb{N}$ are marked bold; the bigram that received the highest weight is precisely in the middle of the text excerpt. A synonym of “risk” or “uncertainty” is written in small caps and surrounded by dashes. $PRisk_{i,t}$ is standardized by its standard deviation, but not capped because they are in the 99th percentile. Duplicate firms are removed from this top list.

Table 3: Transcript excerpts with highest $PRisk_{i,t}$: Panel B

Firm name	$PRisk_{i,t}$ (standardized)	Discussion of political risks associated with:	Call date	$PRisk_{i,t}$ (standardized)	Text surrounding bigram with highest weight ($f_{b,\mathbb{P}}/B_{\mathbb{P}}$)
Nanogen, Inc.	51.89	- FDA approval of company products.	8-Aug-2007	51.89	a dip in revenues during q related to the — UNCERTAINTY— of government approval for the phase funding of the cdc contract additionally management analyst i wanted to followup on the regu- latory front the states that you had mentioned the — POSSIBILITY — of some positive legislation shape on asphalt the funding is very — IFFY — in all the states so and the private work is very slow operator op- erator future so this is a time of quite — UNCERTAINTY — for the states they are not sure what the fmap will be if
World Acceptance Corporation	51.48	- impact of legislation in Texas and other states.	25-Jul-2006	51.48	
United Refining Company	49.27	- effect of government tax refund on bottom line; - state funding of infrastructure projects and the associated demand for asphalt products.	23-Jul-2010	49.27	
Magellan Health Services	49.19	- actions of state Medicaid administrators and insurance regulators; - state procurement of healthcare reform and Federal regulations; - state gubernatorial elections; - Affordable Care Act.	29-Jul-2010	49.19	
Piraeus Bank SA	48.06	- political situation in Greece; - consequences of elections on bank deposits; - relations between EU and Greece, politics of Greece leaving the Euro zone.	19-Mar-2015	48.06	that this time around the process or the impact of the political — uncertainty — has been a bit more subdued than last time
Piedmont Natural Gas	47.98		9-Jun-2009	47.98	your point as you will recall in all three of the states that we have serve jim we are — EXPOSED — only to we have had historically had a very small participation in the political — RISK — market backing only a couple of players parties that magazines when you look at exports that we do to the states no — DOUBT — that is affecting the top and the bottom
Platinum Underwriters Holdings Ltd	46.33	- politics and government decision-making in Kazakhstan and Ukraine; - China's ability to fulfill lending commitments.	18-Feb-2010	46.33	i think largely a result of the — UNCERTAINTY — regarding restructuring of government debt and the general overhang on the weak economy in
Transcontinental Inc.	44.37	- tax reform in Quebec.	14-Sep-2006	44.37	anticipated such — RISKS — and — UNCERTAINTIES — include a dependence on economic and political conditions in israel the impact of competition supply constraints as
Hemisphere Group Inc	44.21	- restructuring of government debt in Puerto Rico.	12-Aug-2014	44.21	
Pointer Telocation Ltd	43.62	- political conditions in Israel.	30-May-2012	43.62	

Notes: This panel lists the top 11-20 transcripts sorted on $PRisk_{i,t}$ together with their associated firm name, earnings call date, $PRisk_{i,t}$ (standardized), a summary of relevant discussions of political risks in the transcript, and the text surrounding the bigram that has received the highest weight in the transcript. Bigrams for which $b \in \mathbb{P}\mathbb{N}$ are marked bold; the bigram that received the highest weight is precisely in the middle of the text excerpt. A synonym of “risk” or “uncertainty” is written in small caps and surrounded by dashes. $PRisk_{i,t}$ is standardized by its standard deviation, but not capped because they are in the 99th percentile. Duplicate firms are removed from this top list.

Table 4: Validation: Implied and realized volatility

PANEL A	Implied volatility $_{i,t}$ (standardized)					
	(1)	(2)	(3)	(4)	(5)	(6)
PRisk $_{i,t}$ (standardized)	0.056*** (0.006)	0.034*** (0.006)	0.033*** (0.006)	0.025*** (0.005)	0.013*** (0.003)	0.016** (0.006)
Mean of PRisk $_{i,t}$ (standardized)		0.262*** (0.004)				
R^2	0.214	0.275	0.394	0.451	0.711	0.783
N	115,059	115,059	115,059	115,059	115,059	18,060
PANEL B	Realized volatility $_{i,t}$ (standardized)					
	(1)	(2)	(3)	(4)	(5)	(6)
PRisk $_{i,t}$ (standardized)	0.048*** (0.005)	0.023*** (0.004)	0.020*** (0.004)	0.020*** (0.004)	0.014*** (0.002)	0.013** (0.006)
Mean of PRisk $_{i,t}$ (standardized)		0.295*** (0.004)				
R^2	0.140	0.224	0.406	0.438	0.621	0.709
N	162,153	162,153	162,153	162,153	162,153	20,816
Time FE	no	no	yes	yes	yes	yes
Sector FE	no	no	no	yes	implied	implied
Firm FE	no	no	no	no	yes	yes
CEO FE	no	no	no	no	no	yes

Notes: This table shows results of panel regressions with realized and implied volatility as the dependent variable in Panels A and B, respectively. Realized volatility $_{i,t}$ is the standard deviation of 90-day stock holding returns of firm i in quarter t and is winsorized as in Stein and Stone (2013). Implied volatility $_{i,t}$ is for 90-day at-the-money options of firm i and time t and is also winsorized as in Stein and Stone (2013). $PRisk_{i,t}$ is our measure for firm-level political risk. Mean of $PRisk_{i,t}$ is the time-average of capped $PRisk_{i,t}$, standardized by its standard deviation in the time series. All regressions control for the log of firm assets. Realized volatility $_{i,t}$, implied volatility $_{i,t}$, and $PRisk_{i,t}$ are standardized by their respective standard deviation. The regression sample in the last column is based on the first quarter of each year due to the annual frequency of CEO information. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 5: Managing political risk

PANEL A	$\frac{I_{i,t}}{K_{i,t-1}} * 100$	$\frac{\Delta \text{capexg}_{i,t}}{\text{capexg}_{i,t-1}} * 100$	$\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$	$\frac{\Delta \text{sales}_{i,t}}{\text{sales}_{i,t-1}} * 100$
	(1)	(2)	(3)	(4)
PRisk _{i,t} (standardized)	-0.159*** (0.041)	-0.338*** (0.120)	-0.769*** (0.155)	-0.075 (0.094)
R ²	0.035	0.041	0.024	0.016
N	119,853	22,520	45,930	173,887
PANEL B	Log(1+\$ donations _{i,t+1})	# of recipients _{i,t+1}	Hedge _{i,t+1}	Log(1+\$ lobby _{i,t+1})
	(1)	(2)	(3)	(4)
PRisk _{i,t} (standardized)	0.087*** (0.018)	0.462*** (0.118)	0.007*** (0.001)	0.186*** (0.027)
R ²	0.250	0.147	0.140	0.268
N	176,173	176,173	176,173	147,228
PANEL C	$\frac{I_{i,t}}{K_{i,t-1}} * 100$	$\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$	Log(1+\$ donations _{i,t+1})	Log(1+\$ lobby _{i,t+1})
	(1)	(2)	(3)	(4)
PRisk _{i,t} (standardized)	-0.223*** (0.059)	-1.064*** (0.230)	0.025 (0.016)	0.168*** (0.032)
PRisk _{i,t} × 1{assets _{i,t} > median assets}	0.149* (0.081)	0.620** (0.289)	0.154*** (0.039)	0.085 (0.056)
N	119,853	45,930	176,173	147,228
Time FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes

Notes: Panel A shows the results from regressions of capital investment (column 1), capital expenditure guidance (column 2), net hiring (column 3), and net sales (column 4) on $PRisk_{i,t}$. Capital investment, $I_{i,t}/K_{i,t-1} * 100$, is calculated recursively using a perpetual-inventory method as described in Stein and Stone (2013). Capex guidance, $\Delta \text{capexg}_{i,t}/\text{capexg}_{i,t-1}$, is the quarter-to-quarter percentage change of the capital expenditure guidance about the closest (usually current) fiscal year-end. We allow for a quarter gap if no guidance (about the same fiscal year-end) was given in the preceding quarter. Net hiring, $\Delta \text{emp}_{i,t}/\text{emp}_{i,t-1} * 100$, is the change in year-to-year employment over last year's value. Net sales is defined similarly on quarterly data. Capital investment and net hiring are winsorized as in Stein and Stone (2013). Capital expenditure guidance and net sales are winsorized at the 1st and 99th percentile. Panel B shows the results of regressions of lobbying and donation activity by firms on $PRisk_{i,t}$. Log(1+\$ donations_{i,t+1}) (column 1) is the log of one plus the sum of all contributions paid to federal candidates; # of recipients_{i,t+1} (column 2) is defined as the number of recipients of donations; hedge_{i,t+1} (column 3) is a dummy variable equal to one if donations to Republicans over donations to Democrats are between the 25th and 75th percentile of the sample; log(1+\$ lobby_{i,t+1}) (column 4) is the log of one plus total lobby expense. In all regressions, $PRisk_{i,t}$ is standardized by its standard deviation. All specifications control for the log of firm assets. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 6: Mean vs. variance of political shocks

PANEL A	$\frac{I_{i,t}}{K_{i,t-1}} * 100$				$\frac{\Delta emp_{i,t}}{emp_{i,t-1}} * 100$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRisk _{<i>i,t</i>} (standardized)	-0.159*** (0.041)	-0.145*** (0.041)	-0.120*** (0.041)	-0.157*** (0.046)	-0.769*** (0.155)	-0.683*** (0.156)	-0.534*** (0.156)	-0.622*** (0.163)
PSentiment _{<i>i,t</i>} (standardized)		0.216*** (0.043)				1.181*** (0.155)		
Sentiment _{<i>i,t</i>} (standardized)			0.454*** (0.048)				2.252*** (0.161)	
Mean stock return 7 days prior _{<i>i,t</i>} (%)				0.025 (0.022)				0.319* (0.166)
Earnings announcement surprise _{<i>i,t</i>}				0.058* (0.032)				0.024*** (0.005)
<i>R</i> ²	0.035	0.035	0.036	0.037	0.024	0.026	0.029	0.026
<i>N</i>	119,853	119,853	119,853	100,661	45,930	45,930	45,930	41,327
PANEL B	Log(1+\$ lobby _{<i>i,t+1</i>})				Log(1+\$ donations _{<i>i,t+1</i>})			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRisk _{<i>i,t</i>} (standardized)	0.186*** (0.027)	0.199*** (0.027)	0.204*** (0.027)	0.217*** (0.031)	0.087*** (0.018)	0.094*** (0.018)	0.097*** (0.018)	0.100*** (0.020)
PSentiment _{<i>i,t</i>} (standardized)		0.203*** (0.032)				0.117*** (0.022)		
Sentiment _{<i>i,t</i>} (standardized)			0.203*** (0.037)				0.115*** (0.026)	
Mean stock return 7 days prior _{<i>i,t</i>} (%)				0.028*** (0.007)				0.012*** (0.004)
Earnings announcement surprise _{<i>i,t</i>}				-0.007 (0.007)				-0.003 (0.004)
<i>R</i> ²	0.268	0.269	0.269	0.291	0.250	0.251	0.251	0.282
<i>N</i>	147,228	147,228	147,228	121,650	176,173	176,173	176,173	147,521
PANEL C	# of recipients _{<i>i,t+1</i>}				Hedge _{<i>i,t+1</i>}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRisk _{<i>i,t</i>} (standardized)	0.462*** (0.118)	0.491*** (0.121)	0.509*** (0.121)	0.512*** (0.136)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.008*** (0.001)
PSentiment _{<i>i,t</i>} (standardized)		0.474*** (0.100)				0.008*** (0.001)		
Sentiment _{<i>i,t</i>} (standardized)			0.541*** (0.131)				0.007*** (0.002)	
Mean stock return 7 days prior _{<i>i,t</i>} (%)				0.032** (0.013)				0.001** (0.000)
Earnings announcement surprise _{<i>i,t</i>}				0.011 (0.013)				-0.000 (0.000)
<i>R</i> ²	0.147	0.148	0.149	0.172	0.140	0.141	0.141	0.158
<i>N</i>	176,173	176,173	176,173	147,521	176,173	176,173	176,173	147,521

Notes: In all regressions, PRisk_{*i,t*}, PSentiment_{*i,t*}, and Sentiment_{*i,t*} are standardized by their standard deviation. Mean stock return 7 days prior_{*i,t*} is the average stock return for the 7 days prior to the earnings call of firm *i* at date *t*. Earnings announcement surprise_{*i,t*} is defined as (EPS_{*i,t*} - EPS_{*i,t-4*})/price_{*i,t*}, where EPS_{*i,t*} are earnings per share (basic) of firm *i* at time *t* and price_{*i,t*} is the closing price of quarter *t*. The remaining variables are defined as in the preceding tables. All specifications control for the log of firm assets, sector, and time fixed effects. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 7: Falsification exercise: Political risk, non-political risk, and political exposure

PANEL A	$\frac{I_{i,t}}{K_{i,t-1}} * 100$			$\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$		
	(1)	(2)	(3)	(4)	(5)	(6)
PRisk _{i,t} (standardized)	-0.143*** (0.041)	-0.082** (0.042)	-0.071 (0.045)	-0.669*** (0.156)	-0.426*** (0.162)	-0.385** (0.182)
NPRisk _{i,t} (standardized)		-0.256*** (0.043)			-0.857*** (0.166)	
Risk _{i,t} (standardized)			-0.138** (0.059)			-0.516** (0.209)
R ²	0.035	0.036	0.035	0.026	0.027	0.026
N	119,853	119,853	119,853	45,930	45,930	45,930
PANEL B	Log(1+\$ lobby _{i,t+1})			Log(1+\$ donations _{i,t+1})		
	(1)	(2)	(3)	(4)	(5)	(6)
PRisk _{i,t} (standardized)	0.199*** (0.027)	0.205*** (0.027)	0.214*** (0.028)	0.095*** (0.018)	0.096*** (0.018)	0.109*** (0.019)
NPRisk _{i,t} (standardized)		-0.025 (0.022)			-0.005 (0.015)	
Risk _{i,t} (standardized)			-0.028 (0.037)			-0.026 (0.027)
R ²	0.269	0.269	0.269	0.251	0.251	0.251
N	147,228	147,228	147,228	176,173	176,173	176,173
PANEL C	# of recipients _{i,t+1}			Hedge _{i,t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)
PRisk _{i,t} (standardized)	0.495*** (0.121)	0.506*** (0.122)	0.446*** (0.109)	0.007*** (0.001)	0.008*** (0.001)	0.007*** (0.001)
NPRisk _{i,t} (standardized)		-0.045 (0.052)			-0.001 (0.001)	
Risk _{i,t} (standardized)			0.092 (0.101)			0.001 (0.002)
R ²	0.148	0.148	0.148	0.141	0.141	0.141
N	176,173	176,173	176,173	176,173	176,173	176,173

Notes: This table probes the information content of $PRisk_{it}$'s logical components. $PRisk_{i,t}$ is our standard measure of political risk; $NPRisk_{i,t}$ (non-political risk) is calculated in the same way as $PRisk_{i,t}$, but based on non-political bigrams instead of political bigrams; and $Risk_{i,t}$ counts the number of synonyms of "risk" or "uncertainty" irrespective of whether they are near a political bigram. As with $PRisk_{i,t}$, all measures are relative to the transcript length. All other variables are defined as in the preceding tables. Each regression specification controls for $PSentiment_{i,t}$, the log of firm assets, as well as time and sector fixed effects. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 8: Variance decomposition of $PRisk_{it}$

	(1)	(2)	(3)
	2-digit SIC	3-digit SIC	4-digit SIC
Sector granularity			
Time FE (aggregate)	0.81%	0.81%	0.81%
Sector FE	4.38%	6.31%	6.87%
Sector \times time FE	3.12%	9.95%	13.99%
“Firm-level”	91.69%	82.93%	78.33%
Permanent differences across firms within sectors (Firm FE)	19.87%	17.52%	16.82%
Variation over time in identity of firms within sectors most affected by political risk (residual)	71.82%	65.41%	61.51%
Number of sectors	65	258	407

Notes: This table shows tabulations of the R^2 from a projection of $PRisk_{i,t}$ on various sets of fixed effects. Column 1 corresponds to our standard specification, using 65 (2-digit SIC) sectors. Columns 2 and 3 use a more granular definition of sectors at 3-digit and 4-digit level, respectively. The “firm-level” variation at the annual level is 89.47%, 82.12%, and 78.38% at the 2-digit, 3-digit, and 4-digit SIC level, respectively.

Table 9: Measurement error

PANEL A: OVERALL VARIATION	$PRisk_{i,t}$ (standardized)			
	(1)	(2)	(3)	(4)
PRisk $_{i,t-1}$ (standardized)	0.475*** (0.005)	0.924*** (0.033)	0.958*** (0.039)	0.813*** (0.011)
N	31,906	31,906	26,811	34,101
Specification	OLS	IV	IV	IV
Instrument		$PRisk10K_{i,t-1}$	$PRisk10K_{i,t-2}$	$PRisk_{i,t-2}$
Implied share M.E.		0.485 (0.018)	0.496 (0.019)	0.406 (0.015)
PANEL B: FIRM-LEVEL VARIATION	$PRisk_{i,t}$ (standardized)			
	(1)	(2)	(3)	(4)
PRisk $_{i,t-1}$ (standardized)	0.422*** (0.005)	0.913*** (0.056)	0.934*** (0.068)	0.781*** (0.013)
N	31,883	31,883	26,789	34,079
Specification	OLS	IV	IV	IV
Instrument		$PRisk10K_{i,t-1}$	$PRisk10K_{i,t-2}$	$PRisk10K_{i,t-2}$
Implied share M.E.		0.538 (0.025)	0.541 (0.028)	0.445 (0.017)

Notes: This table shows AR(1) regressions of $PRisk_{i,t+1}$ at the annual level. In columns 2-4, $PRisk_{i,t}$ is instrumented by the variable indicated in the column. The implied share measurement error of columns 2-4 is calculated as $1 - (\hat{\beta}_{OLS}/\hat{\beta}_{IV})$ where $\hat{\beta}_{OLS}$ is the estimated coefficient in $PRisk_{i,t+1} = \alpha + \beta PRisk_{i,t} + \varepsilon$ and where $\hat{\beta}_{IV}$ is the coefficient on the instrumented $PRisk_{i,t}$ in the same specification. The implied share measurement error of column 5 is calculated as $1 - (\hat{\beta}_{OLS}^2/\hat{\gamma})$ where $\hat{\beta}_{OLS}$ is the same coefficient estimate as before, and where $\hat{\gamma}$ is the estimated coefficient in $PRisk_{i,t+1} = \delta + \gamma PRisk_{i,t-1} + v$. To obtain bootstrapped standard errors, we repeat the following procedure 500 times: draw a random sample of the same size (with replacement and clustered by firm) from our regression sample, run the two regressions, and obtain the implied share measurement error. All specifications control for the log of firm assets. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 10: The nature of firm-level political risk

PANEL A	Implied volatility $_{i,t}$ (standardized)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PRisk $_{i,t}$ (std.)	0.027*** (0.005)	0.026*** (0.005)	0.026*** (0.005)	0.027*** (0.005)	0.027*** (0.005)	0.029*** (0.005)	0.029*** (0.005)
$\beta_i \times$ mean of PRisk $_{i,t}$ (std.)		0.001 (0.003)					
$\beta_{i,t}$ (2-year rolling) \times mean of PRisk $_{i,t}$ (std.)			-0.000 (0.000)				
EPU beta $_i \times$ mean of PRisk $_{i,t}$ (std.)				0.414 (4.764)			
EPU beta (2-year rolling) $_{i,t} \times$ mean of PRisk $_{i,t}$ (std.)					0.017 (0.063)		
Log(1+\$ federal contracts $_{i,t}$)						-0.013*** (0.001)	-0.006 (0.005)
Log(1+\$ federal contracts $_{i,t}$) \times mean of PRisk $_{i,t}$ (std.)							-0.001 (0.001)
R^2	0.501	0.502	0.500	0.501	0.501	0.506	0.506
N	115,059	114,999	110,164	114,979	114,617	115,059	115,059
PANEL B	Realized volatility $_{i,t}$ (standardized)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PRisk $_{i,t}$ (std.)	0.020*** (0.004)	0.019*** (0.004)	0.020*** (0.004)	0.020*** (0.004)	0.020*** (0.004)	0.021*** (0.003)	0.021*** (0.003)
$\beta_i \times$ mean of PRisk $_{i,t}$ (std.)		-0.000 (0.000)					
$\beta_{i,t}$ (2-year rolling) \times mean of PRisk $_{i,t}$ (std.)			0.000 (0.000)				
EPU beta $_i \times$ mean of PRisk $_{i,t}$ (std.)				9.464*** (1.276)			
EPU beta (2-year rolling) $_{i,t} \times$ mean of PRisk $_{i,t}$ (std.)					-0.163*** (0.014)		
Log(1+\$ federal contracts $_{i,t}$)						-0.010*** (0.001)	0.003 (0.004)
Log(1+\$ federal contracts $_{i,t}$) \times mean of PRisk $_{i,t}$ (std.)							-0.002*** (0.001)
R^2	0.490	0.490	0.495	0.490	0.489	0.492	0.493
N	162,153	161,884	153,003	162,153	160,516	162,153	162,153
Time FE	yes	yes	yes	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes	yes	yes	yes
Sector \times time FE	yes	yes	yes	yes	yes	yes	yes

Notes: This table is similar to Table 4. It shows results of panel regressions with realized and implied volatility as the dependent variable in Panels A and B, respectively. EPU beta $_{i,t}$ is a firm-specific beta obtained from a regression of the firm's daily stock returns on Baker, Bloom, and Davis' daily Economic Policy Uncertainty (EPU) Index; EPU beta (2-year rolling) $_{i,t}$ is a firm-quarter specific beta obtained from a regression of the firm's daily stock returns on Baker, Bloom, and Davis' daily EPU Index on a rolling sample of 8 quarters prior to the quarter at hand; mean of PRisk $_{i,t}$ is the cross-sectional average of PRisk $_{i,t}$ at each point in time; and log(1+\$ federal contracts $_{i,t}$) is the total amount of federal contracts awarded to firm i in quarter t . All regressions control for the log of firm assets. All remaining variables are defined as in Table 4. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 11: Top bigrams and transcript excerpts for each topic-specific measure of political risk

Topic name	Top fifteen bigrams	Top three text snippets
Economic Policy, Budget & Regulation	minimum wage, balanced budget, legislation provides, bankruptcy bill, medicaid matching, time congress, emergency economic, and discourages, surpluses in, in aid, create jobs, government when, congress does, waste by, government taxes	1) “of <i>the states</i> <i>arent</i> really that <i>significant</i> for us reza vahabzadeh <i>lehman brothers</i> analyst okay but i mean away from <i>minimum wage rates in texas</i> are you seeing <i>wage rates</i> going higher just because of scarcity of <i>labor</i> by any —CHANCE— <i>tilman</i> ” (Landry’s Restaurants on 10-May-2006) 2) “before its all about for many of our franchisees the level of — <i>uncertainty</i> — whether it be on the <i>political front</i> <i>minimum wage</i> different bills being introduced that may impact their profitability that <i>concern still exists for many and while</i> we remain pretty” (Dunkin’ Brands Group Inc on 21-Jul-2016) 3) “to obtain there are a number of <i>encouraging indicators of government support for the institutional</i> construction sector in order to <i>create jobs and invest</i> in an aging infrastructure however with the <i>new administration there</i> remains shortterm —UNCERTAINTY— also the residential <i>housing market</i> ” (Ashtead Group plc on 9-Dec-2008)
Trade	free trade, trade agreement, trade agreements, trade barriers, freetrade agreement, up markets, the andean, globalization is, labor standards, all trade, policy objectives, jordan the, american free, trade relations, duties on	1) “the —risks— <i>moving forward</i> are what happens with the state of <i>government intervention</i> around the <i>world as it pertains to free trade</i> as it <i>pertains to taxing and changing of tax structure of multinational companies</i> and we are <i>obviously</i> trying to <i>influence</i> ” (Procter Gamble Company on 27-Oct-2010) 2) “we continue to look at that <i>project and do what</i> we can while were <i>waiting for approval</i> of our nonfree <i>trade agreement permit</i> that is —PENDING— with the <i>government and</i> were hopeful well <i>get that permit</i> approved soon in the <i>meantime</i> we” (Exxon Mobil Corp on 31-Oct-2013) 3) “on <i>safety in upper</i> without there is some inherent <i>degree of</i> —UNPREDICTABILITY— associated <i>with legislative processes</i> weve been <i>working with the trade associations in europe</i> which is <i>comprised of other companies and other interest groups</i> associated <i>with building</i> the case around <i>healthcare</i> ” (Becton, Dickinson and Company on 24-Jul-2003)
Technology & Infrastructure	street station, fairness doctrine, cyber warfare, on highways, faithbased organizations, human services, require public, and faithbased, proposals during, private entities, the fcc, structurally deficient, hightech ,jobs, highspeed rail, every government	1) “act on their own ultimately <i>letting the courts</i> decide it <i>eschelon wants the states to set rates</i> because we — <i>fear— the fcc will leave</i> special <i>access rates alone</i> while <i>states might insist</i> on costbased rates which is what we prefer a <i>decision</i> ” (Eschelon Telecom, Inc. on 15-May-2006) 2) “i think theres a lot of — <i>uncertainty</i> — out there regarding the <i>regulatory</i> situation both <i>in congress and the courts at the fcc</i> and a lot has happened <i>this year and i would tell</i> you that the <i>vast majority</i> of it has been” (XO HLDGS INC on 29-Oct-2002) 3) “with the monthly audience up yearyear to <i>million in the fall</i> of according to fom <i>public opinion foundation the frequency of internet</i> use grew as well the number of <i>search —</i> QUERIES— on <i>yandex</i> increased yearyear in fourth quarter while we maintained our” (Yandex NV on 22-Feb-2012)
Security & Defense	on terror, from iraq, bin laden, nuclear weapons, our troops, commander in, in chief, al qaeda, weapons of, mass destruction, of military, in afghanistan, constitution to, osama bin, to authorize	1) “the <i>defense side of aerospace</i> defense <i>markets continue</i> to have —UNCERTAINTY— for due to limited <i>budgets and the winding down of military</i> activities in <i>iraq and afghanistan and</i> we continue to <i>watch for the effects of government budget cuts</i> specifically we are” (CIRCOR International Inc on 05-May-2011) 2) “that are really <i>relevant in todays</i> <i>defense and intelligence</i> market there are <i>vagaries</i> and —UNCERTAINTIES— to the <i>government budget</i> but <i>the intelligence and surveillance and</i> reconnaissance the <i>isr world will remain a high area of government investment</i> as we <i>move forward and</i> ” (PAR Technology Corp on 30-Mar-2016) 3) “all of our <i>markets</i> since <i>businesses</i> have less clarity about the <i>future the impact</i> of a <i>struggling economy the —threat— of war</i> along with <i>record budget deficits in many of the states</i> where we operate is proving to be as challenging as” (PS Business Parks on 28-Feb-2003)

Notes: This table lists the topic name (column 1), the top 15 bigrams most indicative of each of our eight political topics (the bigrams with the highest $\frac{f_{b,z,T}}{B_{z,T}}$) (column 2), and the text surrounding the highest-scoring bigrams within the three highest-scoring transcripts for each topic (column 3). The bigram in question is underlined and in the middle of the text excerpt, topic bigrams are in italic, and political bigrams (such that $b \in \mathbb{P} \setminus \mathbb{N}$) are in bold. A synonym of “risk” or “uncertainty” is written in small caps and surrounded by dashes. Duplicate firms are removed from the text excerpt list.

Table 11: Top bigrams and transcript excerpts for each topic-specific measure of political risk (continued)

Topic name	Top fifteen bigrams	Top three text snippets
Health	prescription drug, cut medicare, government takeover, drug plan, for lowincome, health care, human services, medicare prescription, have health, generic drugs, schip benefits, like medicaid, provide health, of health, health insurance	<p>1) “the internet site of the <i>commission</i> at http://www.segov these —risks— and —UNCERTAINTIES— include among others the impact of the <i>medicare prescription drug improvement act</i> of and other healthcare reforms and initiatives possible reductions of changes in <i>reimbursements</i> from form ph of <i>government</i>” (Medcath Corporation on 12-Aug-2004)</p> <p>2) “rate reduction built into the <i>states fiscal budget</i> for later this year and the state has also reinstated its <i>child health insurance plan program</i> there is still the rate reduction —PENDING— for this october that we have to contend with our team” (American Dental Partners on 27-Jul-2010)</p> <p>3) “remain —UNCERTAIN— however are the regulations that will govern such changes to the healthcare industry <i>reimbursement rate expansion of government health insurance programs</i> new payment systems the effectiveness and lasting power of valuebased reimbursement and payforperformance incentives and the cost of the” (Healthcare Realty Trust Inc on 02-May-2012)</p>
Environment	air act, from renewable, climate change, clean air, states rights, greenhouse gas, nuclear power, nations energy, foreign oil, with opec, global warming, energy independence, legislators are, emissions from, carbon emissions	<p>1) “from convincing to compelling the most recent scientific report issued by the <i>united nations</i> foundation has dispelled any lingering —doubt— <i>climate change is real</i> it is pervasive and the time to begin acting is now both <i>public opinion</i> and the <i>body politic</i>” (Exelon Corporation on 25-Apr-2007)</p> <p>2) “to be the case for that will be very similar to or <i>virtually identical</i> to thereafter we are —unsure— the <i>clean air act program</i> provides that the <i>states should</i> figure out how to do this and how they will go about it” (GenOn Energy Inc on 09-Nov-2011)</p> <p>3) “<i>stabilize</i> is that throughout the <i>three states</i> or have you seen —VARYING— improvements in the different regions tom skains piedmont <i>natural gas</i> chairmen president ceo yes we believe its what weve noticed and our <i>observation</i> is its proportional among the <i>states that</i>” (Piedmont Natural Gas on 9-Sep-2010)</p>
Tax Policy	estate tax, tax relief, bush tax, the estate, middleclass tax, continued unfair, full repeal, typical american, increase taxes, raise taxes, tax cuts, largest budget, repeals the, tax reform, tax cut	<p>1) “quantitative easing coming to an end a budget crisis coming theres been a lot of <i>government money</i> being thrown around <i>tax relief</i> thrown around thats stimulating spending i think there is a lot of —<i>uncertainty</i>— on okay what is going to happen” (Novellus Systems Inc on 27-Apr-2011)</p> <p>2) “there are theres the —<i>suspicion</i>— that there will be in congress an attempt to remove the sunset provision from the <i>estate tax</i> as you know the way its currently drafted it goes away in for one year and comes back into full” (Manulife Financial Corporation on 4-Feb-2003)</p> <p>3) “corp president i wouldnt equate the potential <i>win</i> by <i>de blasio</i> in november as in any way connected to real <i>estate tax</i> increase i think everyone always has a —FEAR— with <i>incumbents</i> and with <i>new administrations</i> that <i>real estate taxes</i> become a” (SL Green Realty Corp on 24-Oct-2013)</p>
Institutions & Political Process	campaign finance, constitution to, finance reform, federal elections, appropriations bills, political system, constitution and, public financing, of voters, in politics, on immigration, constitution the, presidential elections, federal election, political parties	<p>1) “president and ceo absolutely yes andrew marcus deutsche banc securities analyst i —DOUBT— for obviously there has been some <i>campaign finance reform</i> how do you think it is going to affect the <i>political trends</i> in david j barrett hearstargyle television inc president” (Hearst-Argyle Television, Inc. on 30-Oct-2002)</p> <p>2) “introduced during our visits on the hill we continue to hear a <i>resounding support</i> for private capital in overall <i>housing finance reform efforts</i> obviously the <i>fla</i> has already taken steps to decrease its —risk— and the ultimate —risk— to <i>taxpayers</i> by implementing” (Radian Group Inc on 05-May-2011)</p> <p>3) “<i>states</i> that awards are —PENDING— meaning our fees <i>have come out</i> and the <i>states</i> are making decisions we hope to be considered if <i>not win more</i> than half of those so i think we are going to see more rac activity throughout” (HMS Holdings Corp on 29-Apr-2011)</p>

Notes: This table (continued from the previous page) lists the topic name (column 1), the top 15 bigrams most indicative of each of our eight political topics (the bigrams with the highest $\frac{f_b}{B_{b,T}} \log(Z/f_b, z)$) (column 2), and the text surrounding the highest-scoring bigrams within the three highest-scoring transcripts for each topic (column 3). The bigram in question is underlined and in the middle of the text excerpt, topic bigrams are in italic, and political bigrams (such that $b \in \mathbb{P} \setminus \mathbb{N}$) are in bold. A synonym of “risk” or “uncertainty” is written in small caps and surrounded by dashes. Duplicate firms are removed from the text excerpt list.

Table 12: Topic-specific lobbying and topic-specific political risk

PANEL A	$\mathbb{1}[\text{lobbying}_{i,t+1}^T > 0] * 100$				
	(1)	(2)	(3)	(4)	(5)
$\text{PRisk}_{i,t}^T$ (standardized)	1.350*** (0.094)	1.050*** (0.093)	0.794*** (0.047)	0.819*** (0.048)	0.114*** (0.029)
R^2	0.105	0.127	0.311	0.316	0.647
N	1,177,824	1,177,824	1,177,824	1,177,824	1,177,824
PANEL B	$\text{Log}(1+\$ \text{lobby}_{i,t+1}^T)$				
	(1)	(2)	(3)	(4)	(5)
$\text{PRisk}_{i,t}^T$ (standardized)	0.169*** (0.013)	0.133*** (0.013)	0.098*** (0.006)	0.101*** (0.006)	0.015*** (0.004)
R^2	0.119	0.141	0.352	0.357	0.679
N	1,177,824	1,177,824	1,177,824	1,177,824	1,177,824
Time FE	yes	yes	yes	yes	yes
Sector FE	yes	yes	implied	implied	implied
Topic FE	no	yes	yes	yes	yes
Firm FE	no	no	yes	yes	yes
Sector*time FE	no	no	no	yes	yes
Firm*topic FE	no	no	no	no	yes

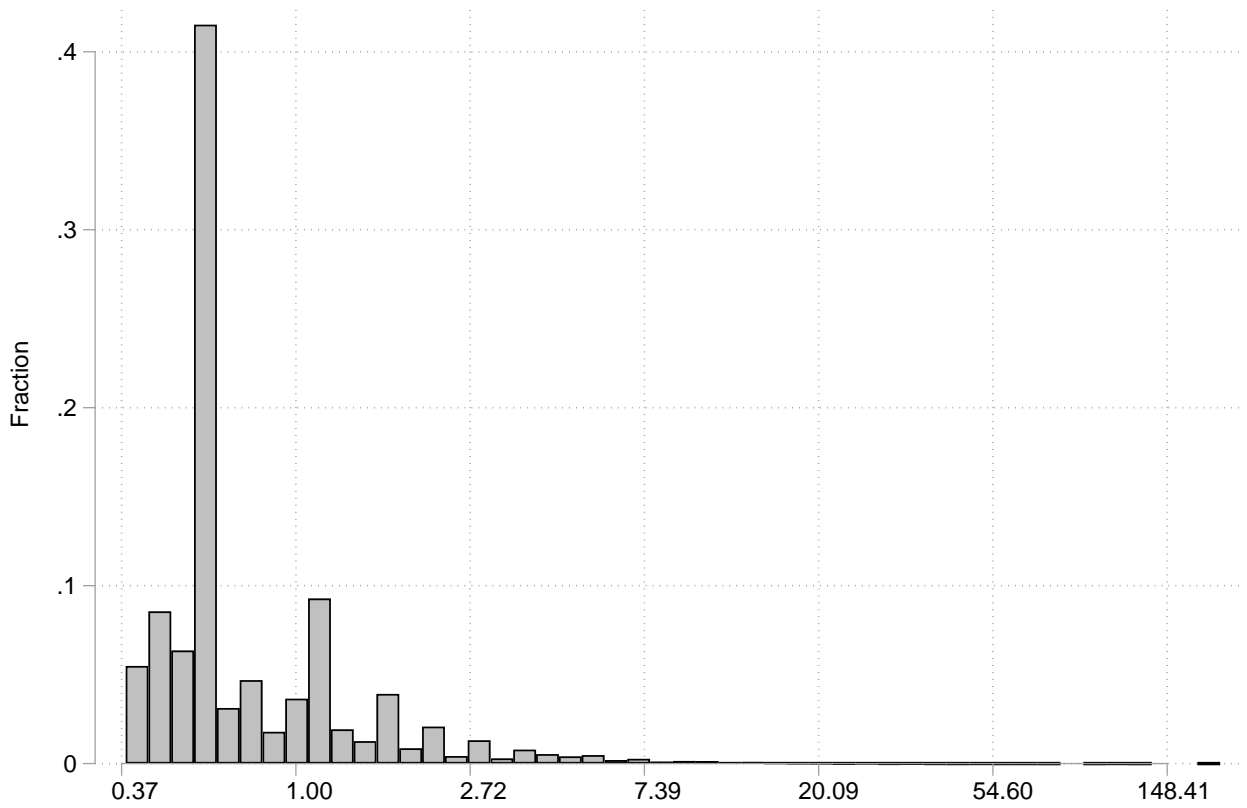
Notes: This table shows the results from regressions of a dummy variable that is one if firm i lobbies on topic T in quarter $t + 1$ (Panel A) and the log of one plus the firm's lobbying expenditure on topic T in quarter $t + 1$ (Panel B) on the firm's topic-specific political risk in quarter t . The dependent variable in Panel B is calculated under the assumption that firms spread their lobbying expenditure evenly across all topics on which they lobby in a given quarter. Lobbying is semi-annual for all pre-2008 quarters. $\text{PRisk}_{i,t}^T$ is standardized by its standard deviation. All specifications control for the log of firm assets. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table 13: Case studies: Obama-era budget crises

PANEL A	$\Delta \text{PRisk}_{i,t}^{\text{ep\&r}}$			$\text{PRisk}_{i,t}^{\text{ep\&r}}$
	(1)	(2)	(3)	(4)
# of 'debt ceiling'	0.257*** (0.075)	0.506*** (0.190)	0.468*** (0.155)	
# of 'fiscal cliff'		0.018 (0.048)		
# of 'government shutdown'			0.129*** (0.049)	
# of 'debt ceiling', 'fiscal cliff', and 'government shutdown'				0.253*** (0.023)
Time FE	no	no	no	yes
Firm FE	no	no	no	yes
Time×sector FE	no	no	no	yes
Sample period	2011-q3	2013-q1	2013-q4	All
R^2	0.009	0.007	0.027	0.316
N	3,342	2,891	2,967	147,228
PANEL B	$\mathbb{1}[\text{lobbying}_{i,t+1}^T > 0] * 100$			$\text{Log}(1+\$ \text{lobbying}_{i,t}^{\text{ep\&r}})$
	(1)	(2)	(3)	(4)
# of 'debt ceiling', 'fiscal cliff', and 'government shutdown'	0.698** (0.299)			
$\text{PRisk}_{i,t}^{\text{ep\&r}}$		0.183** (0.084)	2.430*** (0.937)	0.303*** (0.106)
Time FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Time×sector FE	yes	yes	yes	yes
Sample period	All	All	All	All
Model	OLS	OLS	IV	IV
F-statistic on instruments			76.786	76.786
R^2	0.679	0.679	0.676	0.719
N	147,228	147,228	147,228	147,228

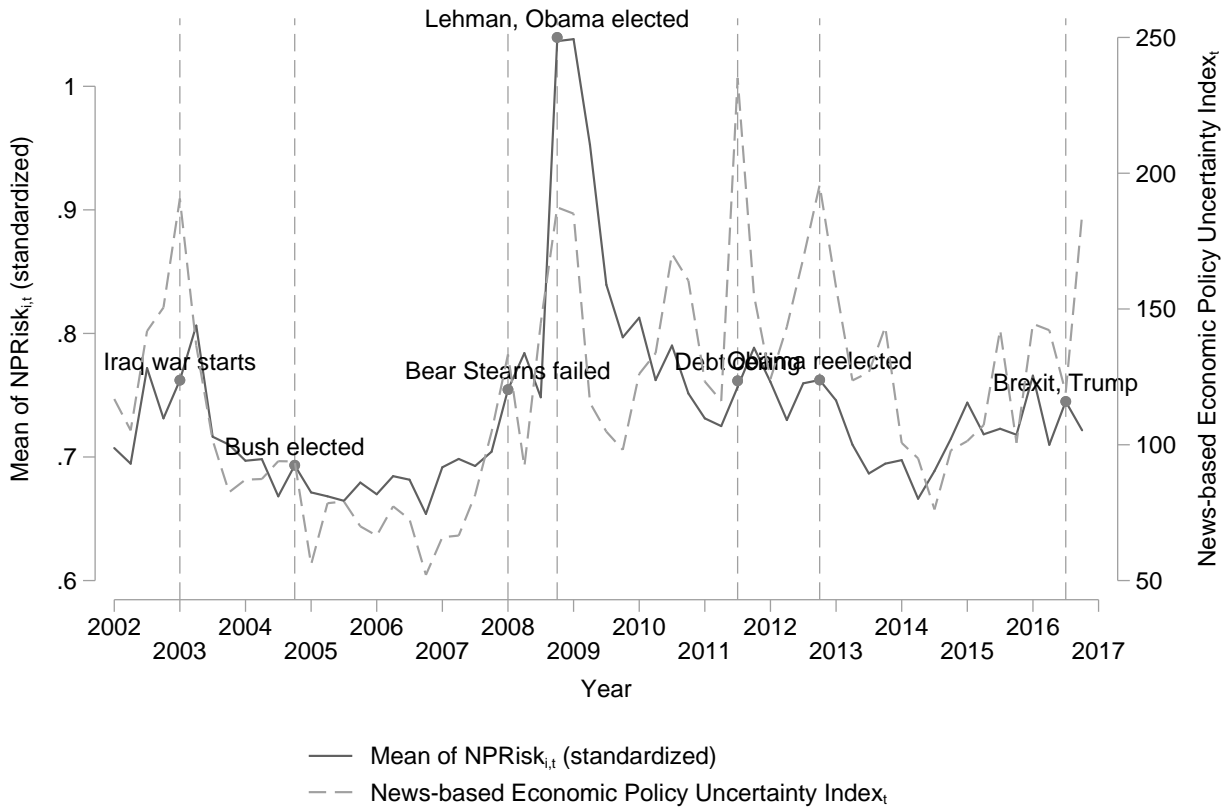
Notes: The regressions in columns 1, 2, and 3 of Panel A are restricted to 2011-q3, 2013-q1, 2013-q4, respectively. $\text{PRisk}_{i,t}^{\text{ep\&b}}$, where “ep&b” stands for topic “economic policy & budget,” is standardized by its standard deviation in the panel. In columns 3 and 4 of Panel B, $\text{PRisk}_{i,t}^{\text{ep\&b}}$ is instrumented by # of ‘debt ceiling’, # of ‘fiscal cliff’, # of ‘government shutdown’; # of ‘debt ceiling’, ‘fiscal cliff’, and ‘government shutdown’ together; and their second- and third-order polynomials. The dummy variable $\mathbb{1}[\text{lobbying}_{i,t+1}^{\text{ep\&r}} > 0] * 100$, where “ep&r” likewise stands for topic “economic policy & budget,” is multiplied by 100 for readability. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively. A pooled OLS regression of # of ‘debt ceiling’, ‘fiscal cliff’, and ‘government shutdown’ on a firm’s share in revenue from government contracts, using all firms and quarters, gives a coefficient (standard error) of .154***(.059, clustered by firm).

Appendix Figure 1: Term frequency of political bigrams ($\mathbb{P} \setminus \mathbb{N}$) in earnings call transcripts



Notes: This figure plots a histogram of the log of bigram scores $(f_{b,\mathbb{P}}/B_{\mathbb{P}}) \times 10^5$. The number of bigrams is 69,818. The mean, median, standard deviation, min, and max of $(f_{b,\mathbb{P}}/B_{\mathbb{P}}) \times 10^5$ are 1.048, 0.586, 2.128, 0.376, 201.15, respectively.

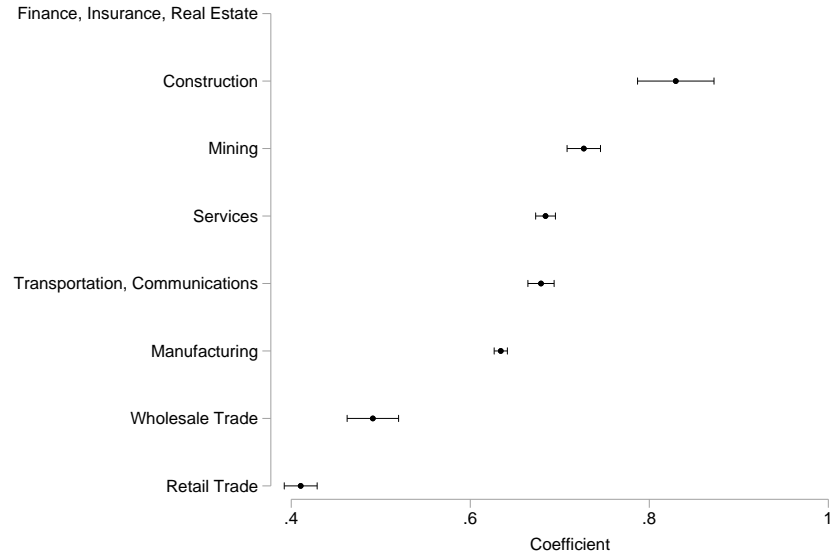
Appendix Figure 2: Time-series of non-political risk ($NPRisk_{i,t}$)



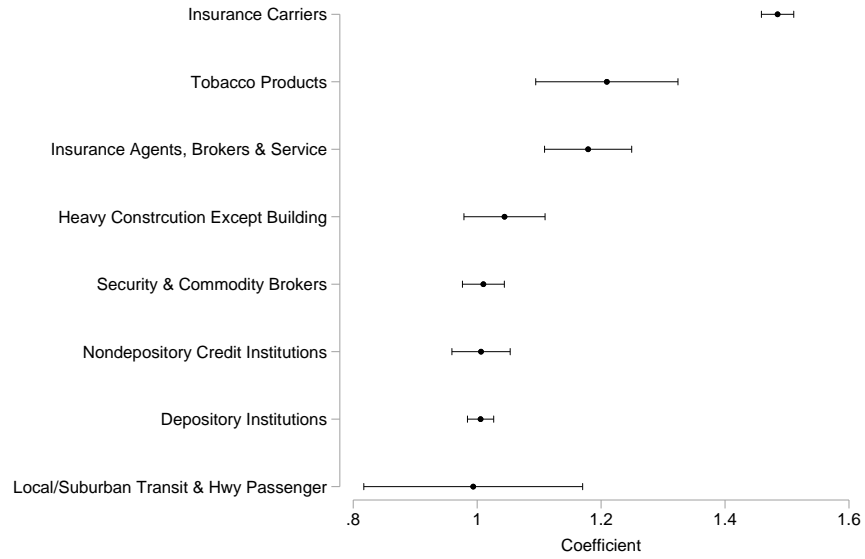
Notes: This figure shows the mean of $NPRisk_{i,t}$ (standardized) across firms in each quarter together with the news-based Economic Policy Uncertainty Index developed by Baker, Bloom, and Davis (2016). The Pearson correlation between the two series is 0.538 with a p-value of 0.000. $NPRisk_{i,t}$ is standardized by its standard deviation in the panel. The Pearson correlation between the mean of $NPRisk_{i,t}$ and the Chicago Board Options Exchange Volatility Index (CBOE VIX) is 0.846 with a p-value of 0.000.

Appendix Figure 3: Mean of $PRisk_{i,t}$ across sectors

Panel A: 1-digit SIC divisions



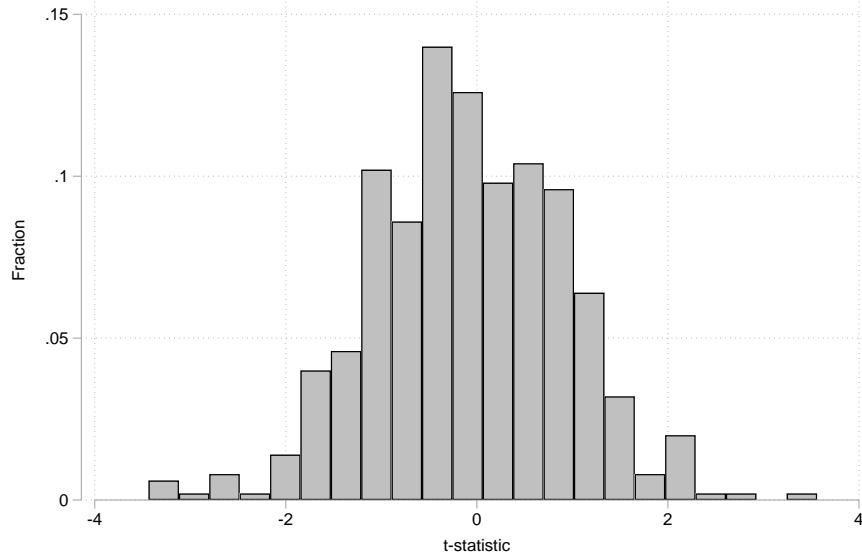
Panel B: 2-digit SIC sectors with highest mean of $PRisk_{i,t}$



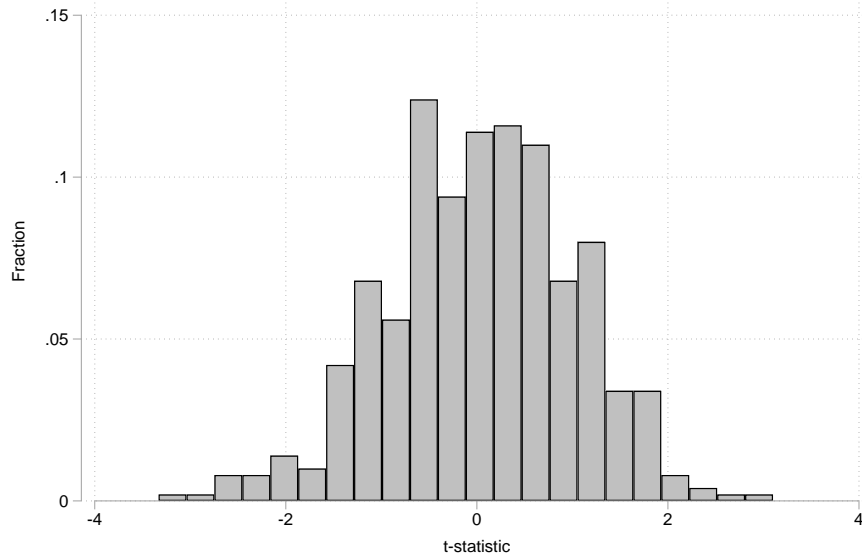
Notes: This figure plots the coefficients and 95% confidence intervals from a projection of $PRisk_{i,t}$ (standardized) on a complete set of sector dummies without a constant. In Panel A, we use a dummy for each 1-digit SIC divisions; in Panel B, we use a dummy for each 2-digit SIC sector. In both panels we plot the top 8 coefficients. $PRisk_{i,t}$ is standardized by its standard deviation.

Appendix Figure 4: Distribution of t-statistics from placebo regressions

Panel A: Firm-quarter unit of analysis

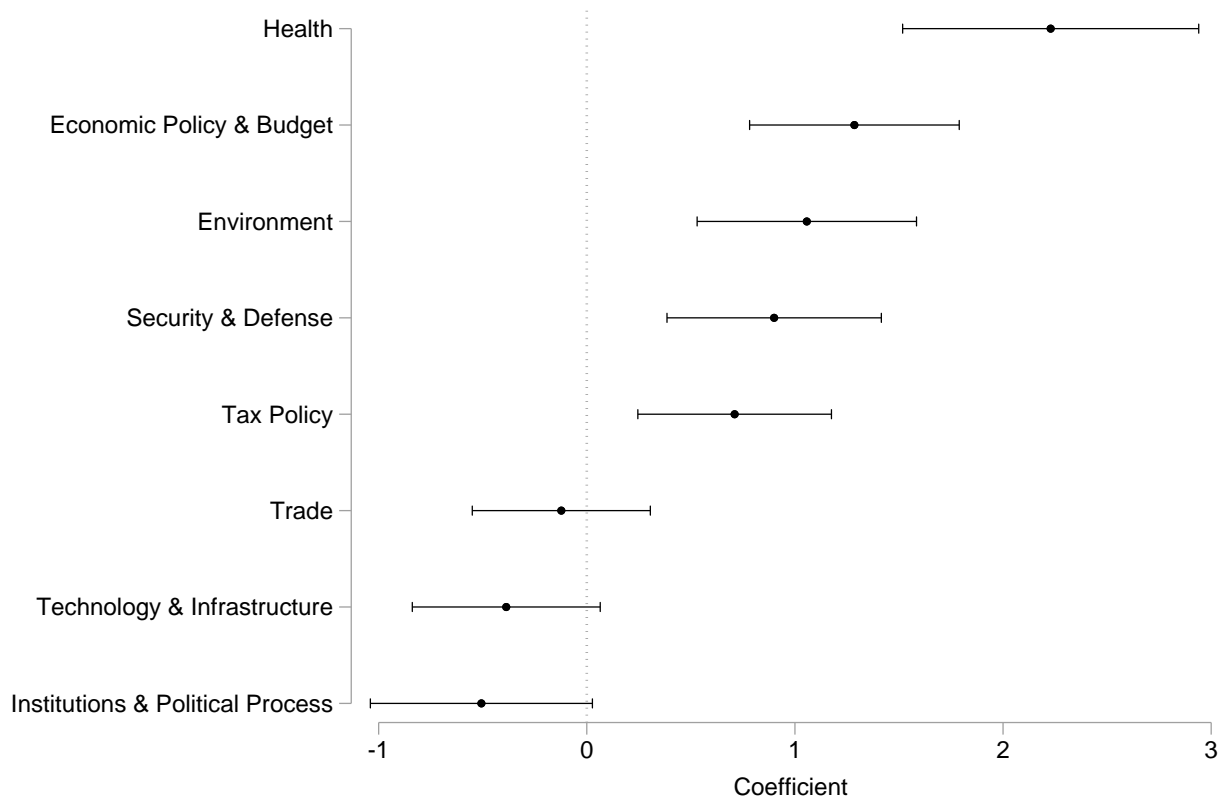


Panel B: Firm-topic-quarter unit of analysis



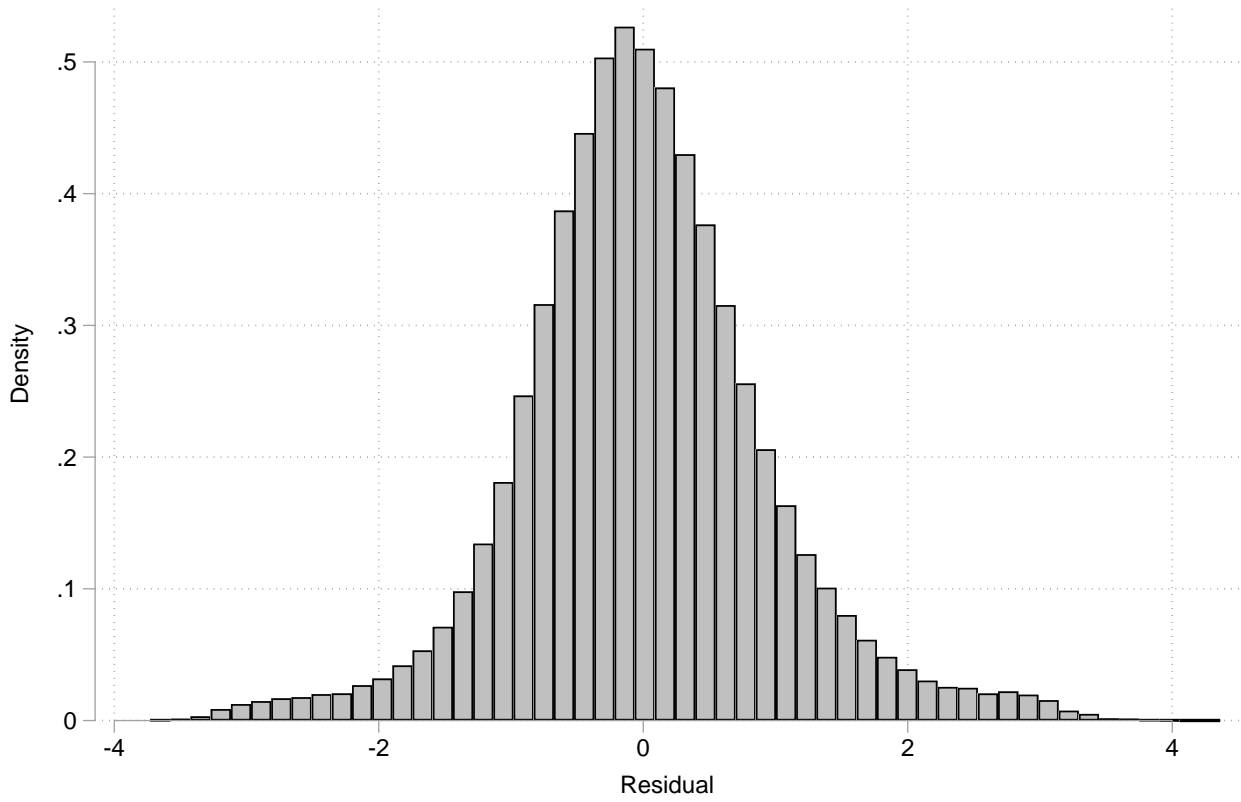
Notes: Panel A plots a histogram of the t-statistics from 500 regressions of realized volatility i,t (standardized) on $PRisk_{i,t}$ (as in column 4 of Table 4) where the time series of $PRisk_{i,t}$ belonging to a given firm has been randomly assigned (with replacement). Standard errors are clustered at the firm level. The number of false positives and negatives at the two-sided 95% confidence interval is 2.8 and 2.60 percent, respectively. Panel B plots a histogram of the t-statistics from 500 regressions of $\mathbb{1}[\text{lobbying}_{i,t+1}^T > 0] * 100$ on $PRisk_{i,t}^T$ (as in column 3 of Table 12) where the time series of $PRisk_{i,t}^T$ belonging to a given firm-topic unit has been randomly assigned (with replacement). Standard errors are clustered at the firm level. The number of false positives and negatives at the two-sided 95% confidence interval is 1.4 and 3.20 percent, respectively.

Appendix Figure 5: Elasticity of lobbying with respect to topic-specific political risk



Notes: This figure plots the coefficients and their 95% confidence intervals of $topic^T \times PRisk_{i,t}^T$ for $T = \{1, \dots, 8\}$ from a regression of $\mathbb{1}[\text{lobbying}_{i,t+1}^T > 0] * 100$ on $topic^T \times PRisk_{i,t}^T$ (standardized) for $T = \{1, \dots, 8\}$, firm, topic, time fixed effects, and log of firm assets. The variables $topic^T$ are dummy variables for each given topic. $PRisk_{i,t}^T$ is standardized by its standard deviation. Standard errors are double clustered at the firm and topic level.

Appendix Figure 6: Distribution of firm-level political sentiment



Notes: This histogram plots the distribution of the residuals from a projection of $PSentiment_{i,t}$ (standardized) on sector fixed effects, time fixed effects, and the interaction of time and SIC2-digit sector fixed effects. The standard deviation of the distribution is .947; the skewness is .166.

Appendix Table 1: Mapping of political topics to Center for Responsive Politics (CRP) lobbying issues

Political topic	Lobbying issues
Economic Polic & Budget	Accounting; Advertising; Apparel, Clothing, & Textiles; Arts & Entertainment; Automotive Industry; Aviation, Airlines & Airports; Banking; Bankruptcy; Beverage Industry; Chemical Industry; Consumer Product Safety; Copyright, Patent & Trademark; District of Columbia; Economics & Economic Development; Federal Budget & Appropriations; Finance; Food Industry; Gaming, Gambling & Casinos; Manufacturing, Insurance; Labor, Antitrust & Workplace; Marine, Boats & Fisheries; Media Information & Publishing; Minting/Money/Gold Standard; Radio & TV Broadcasting; Railroads; Roads & Highways; Small Business; Telecommunications; Tobacco; Transportation; Travel & Tourism; Trucking & Shipping; Unemployment
Environment	Agriculture; Animals; Clean Air & Water; Environment & Superfund; Fuel, Gas & Oil; Hazardous & Solid Waste; Natural Resources; Real Estate & Land Use; Utilities
Trade	Commodities; Foreign Relations; Postal; Tariffs; Trade
Institutions & Political Process	Government Issues; Torts
Health	Health Issues; Medicare & Medicaid; Medical Research & Clinical Labs; Pharmacy
Security & Defense	Defense; Disaster & Emergency Planning; Homeland Security; Intelligence; Veterans Affairs
Tax Policy	Taxes
Technology & Infrastructure	Aerospace; Computers & Information Technology; Science & Technology

Appendix Table 2: Top 100 positive and negative sentiment words in PSentiment_{*i,t*}

word	frequency	word	frequency	word	frequency	word	frequency
good	2,641,408	exciting	125,149	loss	467,845	negatively	58,012
strong	1,722,126	achieving	124,735	decline	429,914	unemployment	56,743
great	1,062,140	enable	120,768	difficult	389,060	worse	56,076
better	1,044,778	successfully	116,105	against	317,498	lag	55,132
opportunities	943,258	efficiencies	110,269	negative	310,768	wrong	55,089
able	828,658	easy	102,912	restructuring	268,455	bridge	54,903
positive	801,637	strengthen	98,139	challenges	251,140	delayed	54,439
progress	767,047	enhanced	88,684	force	214,267	severe	53,619
opportunity	761,564	encouraging	80,381	late	208,239	dropped	51,672
best	586,648	strengthening	79,861	closing	201,021	volatile	50,101
improvement	578,902	innovative	78,270	declined	190,489	lose	49,996
benefit	545,925	stability	74,459	losses	186,988	disclosed	49,461
improve	491,591	excellence	72,222	critical	176,951	shut	48,688
pleased	472,508	satisfaction	70,475	challenging	172,838	complicated	46,154
improved	399,832	pleasure	69,950	weak	147,742	breakdown	45,190
improving	393,062	winning	69,761	closed	141,847	slowing	44,031
success	372,656	superior	68,689	problem	141,206	serious	43,591
effective	337,530	gaining	68,179	claims	140,602	difficulties	42,743
profitability	326,058	perfect	66,669	break	126,092	disclose	42,695
successful	305,358	easier	65,672	slow	121,636	losing	41,206
greater	304,344	alliance	60,327	recall	119,959	slowed	40,555
stronger	301,302	collaboration	60,090	challenge	118,675	stress	40,184
strength	299,641	enabled	59,525	delay	114,017	caution	39,621
advantage	281,246	advantages	54,330	concerned	113,522	disruption	39,382
leadership	273,733	exceptional	53,971	bad	113,416	discontinued	38,879
achieve	259,392	stabilize	51,977	cut	109,198	failure	38,639
despite	250,814	gained	51,765	concern	108,700	challenged	37,776
confident	246,215	strongest	49,524	problems	108,547	downward	37,597
improvements	244,112	accomplished	48,676	litigation	105,754	poor	36,464
achieved	241,412	enhancing	47,817	weakness	103,443	deficit	34,792
excited	236,622	enables	47,758	volatility	103,236	suspect	34,719
favorable	229,367	valuable	47,491	difficulty	99,148	slowly	33,622
stable	226,222	impressive	46,205	lost	98,587	nonperforming	33,240
leading	220,624	progressing	45,966	crisis	97,581	unfavorable	33,165
efficiency	219,873	strengthened	44,440	concerns	93,580	deterioration	30,689
gain	215,827	enjoy	43,041	declines	91,712	opportunistic	30,593
happy	212,745	positively	42,027	weaker	89,910	termination	29,859
optimistic	184,364	efficiently	41,960	delays	87,772	miss	29,821
gains	182,624	exclusive	41,163	impairment	83,706	investigation	29,702
profitable	168,303	achievement	41,120	opposed	81,317	breaking	29,454
innovation	163,060	strengths	41,004	recession	75,221	shortage	29,249
excellent	161,468	enabling	39,380	slowdown	74,771	attrition	28,658
encouraged	153,800	easily	38,297	downturn	74,492	damage	28,519
attractive	151,848	stabilized	38,076	slower	68,496	chargeoffs	28,456
win	147,404	satisfied	37,099	closure	67,907	worst	28,432
efficient	146,568	accomplish	36,791	lack	67,044	drag	28,308
benefited	132,346	benefiting	36,606	unfortunately	65,115	hurt	27,999
highest	131,666	accomplishments	36,427	missed	64,440	disappointed	27,415
tremendous	130,119	transparency	35,139	declining	62,109	bankruptcy	26,730
enhance	126,034	diligently	33,363	adverse	58,552	shutdown	26,657

Total sentiment words found: 40,207,559

This table shows the frequency across all transcripts of all positive and negative sentiment words from Loughran and McDonald (excluding ‘question’, ‘questions’, and ‘ill’) that appear within 10 words of a political but not non-political bigram.

Appendix Table 3: All synonyms found when measuring $\text{PRisk}_{i,t}$

word	frequency	word	frequency	word	frequency
risk	413,925	jeopardize	1,821	riskiness	135
risks	106,858	unsettled	1,664	treacherous	130
uncertainty	91,775	unpredictability	1,563	oscillating	112
variable	68,138	dilemma	1,547	perilous	92
chance	60,863	skepticism	1,502	tentativeness	85
possibility	57,599	hesitancy	1,491	unreliability	72
pending	53,318	riskier	1,352	wariness	70
uncertainties	51,092	unresolved	1,214	vagueness	59
uncertain	39,191	unsure	1,151	dodgy	58
doubt	39,022	irregular	1,123	equivocation	55
prospect	30,926	jeopardy	1,077	indecisive	43
bet	21,279	suspicion	1,027	chancy	40
variability	21,215	risking	863	menace	38
exposed	19,553	peril	660	qualm	35
likelihood	19,280	hesitating	628	vacillating	33
threat	19,021	risked	577	gnarly	32
probability	15,791	unreliable	550	disquiet	30
unknown	12,050	unsafe	486	ambivalence	30
varying	9,442	hazy	472	imperil	28
unclear	9,036	unforeseeable	466	vacillation	22
unpredictable	8,467	apprehension	466	untrustworthy	17
speculative	8,132	halting	453	incalculable	17
fear	7,939	wager	446	diffident	15
reservation	7,026	torn	437	equivocating	15
hesitant	6,275	precarious	362	changeability	11
gamble	6,065	undetermined	349	fickleness	11
risky	5,227	insecurity	348	misgiving	11
instability	4,762	debatable	346	undependable	9
doubtful	4,736	undecided	341	parlous	8
hazard	4,626	dicey	330	fitful	8
tricky	4,359	indecision	324	incertitude	8
sticky	4,325	wavering	266	unconfident	6
dangerous	4,297	iffy	235	defenseless	5
tentative	4,018	faltering	212	unsureness	3
hazardous	3,155	endanger	205	fluctuant	3
queries	2,676	quandary	204	niggle	3
danger	2,465	changeable	189	diffidence	3
fluctuating	2,462	insecure	189	doubtfulness	1
unstable	2,440	riskiest	183	precariousness	1
vague	2,427	hairly	177		
erratic	1,876	ambivalent	169		
query	1,826	dubious	158		

Total synonyms found: 1,287,932

This table shows the frequency across all transcripts of all single-word synonyms of ‘risk’, ‘risky’, ‘uncertain’, and ‘uncertainty’ as given in the Oxford Dictionary (excluding ‘question’, ‘questions and ‘venture’) that appear within 10 words of a political but not non-political bigram.

Appendix Table 4: $PRisk_{it}$ and federal elections

	$PRisk_{i,t}$ (standardized)	
	(1)	(2)
Federal elections $_t$	0.083*** (0.008)	0.021** (0.010)
Presidential elections $_t$		0.133*** (0.016)
Sector FE	yes	yes
Year FE	yes	yes
Number of firms	5,720	5,720
Number of periods	60	60
R^2	0.050	0.050
N	144,340	144,340

Notes: Federal elections $_t$ is a dummy variable equal to one in the fourth quarter of every even year. Presidential elections $_t$ is a dummy variable equal to one in the fourth quarter of 2004, 2008, and 2012. We control for sector and year effects, and the log of firm assets in both regressions. $PRisk_{i,t}$ is standardized by its standard deviation. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 5: Event studies: Brexit and Trump

	$\Delta PRisk_{i,t}$ (standardized)	
	(1)	(2)
# of 'brexit'	0.028*** (0.006)	
# of 'trump', and ('twitter' or 'tweet')		0.140*** (0.038)
# of firms with regressor > 0	954	5
Sample period	2016q3	2016q4
R^2	0.009	0.001
N	3,573	3,527

Notes: This table shows regressions of $\Delta PRisk_{i,t}$ (the difference of a firm's $PRisk_{i,t}$ to the previous quarter) on word counts of 'brexit' (column 1) and word counts of 'trump' together with 'twitter' or 'tweet' (column 2). The regression samples are restricted to 2016-q3 (column 1) and 2016-q4 (column 2). The average number of mentions (for firms with at least one mention) is 6.15 ('brexit') and 6.4 ('trump' and 'twitter', or 'trump' and 'tweet'). Multiplying these numbers with the coefficients above yields the average increases cited in the text: $6.15 \times 0.029 = 0.178$ and $6.40 \times 0.197 = 0.1260$, respectively. Standard errors are robust. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 6: Standard errors: Firm-quarter specifications

	Realized volatility $_{i,t}$ (standardized)			
	(1)	(2)	(3)	(4)
PRisk $_{i,t}$ (standardized)	0.020*** (0.002)	0.020*** (0.007)	0.020*** (0.002)	0.020*** (0.004)
Standard error	robust	clustered by sector	clustered by quarter	clustered by firm
Time FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
R^2	0.438	0.438	0.438	0.438
N	162,153	162,153	162,153	162,153

Notes: $PRisk_{i,t}$ is standardized by its standard deviation. All specifications include log of firm assets as a control. Standard errors are robust in column 1, clustered at the SIC-2 level in column 2, clustered by year-quarter in column 3, and clustered at the firm level in column 4. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 7: Transcript excerpts with highest $PSentiment_{i,t}$

Firm Name	Call Date	$PSentiment_{i,t}$ (standardized)	Discussion of political risks associated with:	Text surrounding bigram with high weight ($f_{b,\mathbb{P}}/B_{\mathbb{P}}$)
Central Vermont Public Service	11-May-2006	20.934	- Firm lobbying and applying for various favorable regulatory changes on electricity rates, etc.	(strength) to choose the (best) options for the companies and the states future energy supply all of these goals are interdependent and
China Mobile Ltd	16-Aug-2012	16.225	- Strong support from government for companys TD-LTE developing activities.	port from the government and industry the company has (successfully) (accomplished) scale trial in six
InterContinental Hotels Group PLC	08-May-2013	14.689	- Dip in China business due to tightened government spending in particular areas expected to be temporary.	proportion of government business in these regions trading in resort locations was (stronger)
China Telecom Corp Ltd	19-Aug-2015	14.034	- Company expects to benefit from national macro policy of Made-in-China 2025 and Internet+.	continue the establishment of nationwide centralized mess to drive management reform and (enhance) (efficiency) third (improve) cost control to (enhance) cost structure
Mercury General	3-Aug-2009	13.820	- Anticipated benefits from proposed legislation for harmonized national insurance regulation.	with one set of rules and standards for all of the states that we do business would probably be a (positive) as
Catalyst Health Solutions, Inc.	29-Jul-2004	13.319	- Confident about prospects of securing additional government contracts, federal drug benefit program likely to also have positive effects.	the pharmacy (benefit) can certainly help the state most of the states are under significant budget pressures and they are looking for
China Unicom Hong Kong Ltd	17-Aug-2016	12.045	False positive	create new growth drivers to deploy premium network and (strengthen) support for frontline and customer services to (strengthen) (innovation) in systems and
Real Goods Solar Inc	23-Aug-2016	11.867	False positive	growth by making key adjustments to our business to (better) address the evolving hawaii solar market we made key additions to our
NiSource Inc	03-Aug-2015	11.847	- Improved opportunities from regulatory efforts in various states, including Indiana and Washington.	pureplay utility our regulatory efforts continue to play out across the states and were very (encouraged) by the (opportunities) we see in
Dover Downs Gaming and Entertainment, Inc.	27-Oct-2005	11.816	- Expect favorable regulatory decision to expand gambling operations, favorable legislation on racetracks.	pretty (good) as well and there was some talk by the legislature of passing some initiatives to help the race-tracks out without
Central Vermont Public Service Corp	09-Nov-2011	11.661	- Improved public support for merger in Vermont Public Service Board, approval from DOJ and FTC for merger.	ensure that the deal is in their (best) interest and the states (best) interest and we are (confident) that the public service
Yanzhou Coal Mining Co Ltd	31-Aug-2015	11.595	- Secured government subsidy, favorable effect of new import restrictions, Positive government actions to combat illegal mining.	number three we are (able) to offer a high amount of government subsidy to be applied in the first half zhongyin financing

Notes: This panel lists the top 12 transcripts sorted on $PSentiment_{i,t}$ together with their associated firm name, earnings call date, $PSentiment_{i,t}$ (standardized), a summary of relevant discussions of political risks in the transcript, and the text surrounding one of top three bigrams that have received the highest weight in the transcript. Bigrams for which $b \in \mathbb{P} \setminus \mathbb{N}$ are marked bold; the bigram for which the weight is used is precisely in the middle of the text except. A synonym of “risk” or “uncertainty” is written in small caps and surrounded by dashes. $PSentiment_{i,t}$ is standardized by its standard deviation. Duplicate firms are removed from this top list.

Appendix Table 8: Transcript excerpts with lowest $PSentiment_{i,t}$

Firm Name	Call Date	$PSentiment_{i,t}$ (standardized)	Discussion of political risks associated with:	Text surrounding bigram with high weight ($f_{b,\mathbb{P}}/B_{\mathbb{P}}$)
ARCTIC GLACIER COME FD Ltd.	12-May-2009	-15.914	- Antitrust action against US packaged ice industry.	production of documents to the doj ((antitrust)) division and to the states attorneys general and is in the process of providing the year later we are being quite candid on these instances of the government ((inaction)) as they are symptoms of the (concerns) held more
Gabriel Resources Ltd.	7-May-2008	-15.078	- Romanian government delays environmental impact assessment, obstructs.	middlesex county ((alleging)) ((violations)) of new jersey consumer ((fraud)) and civil rights laws in each case relating to the marketing and commercialization
Arbitron Inc.	21-Oct-2008	-14.692	- Firm under investigation for insider trading, false advertising, and deceptive business practices.	state medicaid rates as you know many states are projecting budget ((deficits)) the most significant projected ((deficits)) where omega owns facilities are
Omega HealthCare Investors, Inc.	5-Nov-2008	-14.001	- Negative impact of state fiscal situation on medicaid rates.	by the general (improvements) in california where ((serious)) ((concerns)) over the states ability to handle its debt appeared to be ((easing)) ((unfortunately))
Polaris Materials Corp	22-Mar-2012	-13.931	- Government program for surface transportation not re-authorized.	after the epa ((dropped)) their case the railroad commission ((accused)) the epa of quote \rightarrow FEAR \rightarrow mongering gross ((negligence)) and ((severe)) ((mishandling)) unquote
Natural Gas Services Group Inc	10-May-2012	-13.715	- Regulatory action regarding ground water contamination from fracking.	to date have not been (successful) and the florida supreme court has ((declined)) to review ((verdicts)) ((against)) the tobacco industry ((defendants)) while
Vector Group Ltd	24-Feb-2012	-13.632	- FDA action against tobacco industry, regulators not taking action on competitors' tax evasion.	of operating concessions and our subsidiary for airport operation oma the civil construction business is where our biggest ((challenge)) lies civil construction
Empresas ICA SAB de CV	30-Mar-2016	-13.554	False positive	of our expectation due to ((poor)) sales in north america the states and canada are ((critical)) markets for us and we must
Radcom Ltd.	19-Jul-2004	-13.154	False positive	resulting from the sales drop of tamiflu due to ((termination)) of government stockpiling is jpy billion decrease in income due to ((diminished))
Chugai Pharmaceutical Co., Ltd.	22-Apr-2008	-12.593	- Sales drop because termination of government stockpiling of Tamiflu and subsidies for purchases abroad.	high ((unemployment)) tax rates for a while because many of the states funds are ((depleted)) and until they get restored the states
COMFORCE CORP	23-Mar-2010	-12.582	- Negative expected effects of depletion of state unemployment funds.	it ((claims)) the only viable solution is for the us congress to permit a wholesale ((abrogation)) of contracts many of which are
Assured Guaranty Ltd	06-Nov-2015	-12.270	- Concerns about Puerto Rico bankruptcy proceedings.	

Notes: This panel lists the bottom 12 transcripts sorted on $PSentiment_{i,t}$ together with their associated firm name, earnings call date, $PSentiment_{i,t}$ (standardized), a summary of relevant discussions of political risks in the transcript, and the text surrounding one of top three bigrams that have received the highest weight in the transcript. Bigrams for which $b \in \mathbb{P} \setminus \mathbb{N}$ are marked bold; the bigram for which the weight is used is precisely in the middle of the text except. A synonym of “risk” or “uncertainty” is written in small caps and surrounded by dashes. $PSentiment_{i,t}$ is standardized by its standard deviation. Duplicate firms are removed from this top list.

Appendix Table 9: Validation of PSentiment

PANEL A	Av return 7 days prior $_{i,t}$ (%)			
	(1)	(2)	(3)	(4)
PSentiment $_{i,t}$ (standardized)	0.033*** (0.005)	0.027*** (0.005)		-0.010 (0.006)
Sentiment $_{i,t}$ (standardized)			0.058*** (0.005)	0.065*** (0.006)
NPSentiment $_{i,t}$ (standardized)		0.019*** (0.005)		
R^2	0.046	0.046	0.047	0.047
N	148,202	148,202	148,202	148,202
PANEL B	Av return 30 days prior $_{i,t}$ (%)			
	(1)	(2)	(3)	(4)
PSentiment $_{i,t}$ (standardized)	0.029*** (0.002)	0.024*** (0.002)		-0.003 (0.003)
Sentiment $_{i,t}$ (standardized)			0.046*** (0.002)	0.048*** (0.003)
NPSentiment $_{i,t}$ (standardized)		0.017*** (0.002)		
R^2	0.182	0.182	0.183	0.183
N	148,304	148,304	148,304	148,304

Notes: Stock return X days prior $_{i,t}$ is the average stock return for the 7 days (panel A) or 30 days (panel B) prior to the earnings call at date t . In all regressions, Sentiment $_{i,t}$ and PSentiment $_{i,t}$ are standardized by their standard deviation. All specifications control for the log of firm assets, sector, and time fixed effects. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 10: Alternative implementations of $PRisk_{it}$: Correlations

	$PRisk_{i,t}$	Textbook-based $PRisk_{i,t}$	Newspaper-based $PRisk_{i,t}$	Unweighted $PRisk_{i,t}$	$PRisk_{i,t}$ w/o stopwords	Firm-level EPU $_{i,t}$
$PRisk_{i,t}$	1.000					
Textbook-based $PRisk_{i,t}$	0.970	1.000				
Newspaper-based $PRisk_{i,t}$	0.663	0.519	1.000			
Unweighted $PRisk_{i,t}$	0.759	0.681	0.784	1.000		
$PRisk_{i,t}$ w/o stopwords	0.628	0.584	0.596	0.669	1.000	
Firm-level EPU $_{i,t}$	0.190	0.180	0.172	0.199	0.210	1.000

Notes: This table reports correlations between various alternative implementations of $PRisk_{i,t}$. $PRisk_{i,t}$ (standardized) is defined as before; *Textbook-based $PRisk_{i,t}$* (standardized) is like $PRisk_{i,t}$ but based on a list of political bigrams from the textbook-based library that is not appended with political bigrams from the newspaper-based library; *Newspaper-based $PRisk_{i,t}$* (standardized) is like $PRisk_{i,t}$ but based on a list of political bigrams from only the newspaper-based library; *Unweighted $PRisk_{i,t}$* (standardized) counts, like $PRisk_{i,t}$, the number of political bigrams near synonyms divided by the transcript length, but unlike $PRisk_{i,t}$ the numerator is not weighted by the scores of the bigrams; $PRisk_{i,t}$ (standardized) w/o stopwords is constructed exactly as $PRisk_{i,t}$ but based on a version of the training library and earnings transcripts that have been cleaned from a list of stopwords; $PRisk_{i,t}$ (1) is a dummy variable equal to one if the transcript has at least one of the word combinations specified in Baker, Bloom, and Davis (2016).

Appendix Table 11: Alternative implementations of $PRisk_{it}$: Estimations

	Implied volatility $_{i,t}$ (standardized)				Log(1+\$ lobby $_{i,t+1}$)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PANEL A														
$PRisk_{i,t}$ (standardized)	0.025*** (0.005)							0.186*** (0.027)						
Textbook-based $PRisk_{i,t}$ (standardized)		0.022*** (0.005)							0.163*** (0.026)					
Newspaper-based $PRisk_{i,t}$ (standardized)			0.028*** (0.005)							0.209*** (0.027)				
$PRisk_{i,t}$ (standardized, not capped)				0.018*** (0.005)							0.153*** (0.029)			
Unweighted $PRisk_{i,t}$ (standardized)					0.042*** (0.006)							0.174*** (0.031)		
$PRisk_{i,t}$ (standardized) w/o stopwords						0.016*** (0.005)							0.214*** (0.027)	
Firm level EPU $_{i,t}$ (1)							0.019 (0.013)							0.695*** (0.083)
N	115,059	115,059	115,059	115,059	115,059	115,059	115,059	147,228	147,228	147,228	147,228	147,228	147,228	147,228
PANEL B														
	$I_{i,t}/K_{i,t-1} * 100$				$\Delta emp_{i,t}/emp_{i,t-1} * 100$									
$PRisk_{i,t}$ (standardized)	-0.159*** (0.041)													
Textbook-based $PRisk_{i,t}$ (standardized)		-0.161*** (0.040)												
Newspaper-based $PRisk_{i,t}$ (standardized)			-0.096** (0.045)							-0.715*** (0.102)				
$PRisk_{i,t}$ (standardized, not capped)				-0.146*** (0.042)							-0.560*** (0.180)			
Unweighted $PRisk_{i,t}$ (standardized)					-0.175*** (0.049)							-0.935*** (0.176)		
$PRisk_{i,t}$ (standardized) w/o stopwords						-0.127*** (0.042)							-0.795*** (0.152)	
Firm level EPU $_{i,t}$ (1)							-0.303*** (0.114)							-2.577*** (0.672)
N	119,853	119,853	119,853	119,853	119,853	119,853	119,853	45,930	45,930	45,930	45,930	45,930	45,930	45,930
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: This table reports estimation results from replications of key findings using alternative implementations of $PRisk_{i,t}$. $PRisk_{i,t}$ (standardized) is defined as before; *Textbook-based* $PRisk_{i,t}$ (standardized) is like $PRisk_{i,t}$ but based on a list of political bigrams from the textbook-based library that is not appended with political bigrams from the newspaper-based library; *Newspaper-based* $PRisk_{i,t}$ (standardized) is like $PRisk_{i,t}$ but based on a list of political bigrams from only the newspaper-based library; *Unweighted* $PRisk_{i,t}$ (standardized) counts, like $PRisk_{i,t}$, the number of political bigrams near synonyms divided by the transcript length, but unlike $PRisk_{i,t}$ the numerator is not weighted by the scores of the bigrams; $PRisk_{i,t}$ (standardized) w/o stopwords is constructed exactly as $PRisk_{i,t}$, but based on a version of the training library and earnings transcripts that have been cleaned from a list of stopwords; and Firm level EPU $_{i,t}$ (1) is a dummy variable equal to one if the transcript has at least one of the word combinations specified in Baker, Bloom, and Davis (2016). Implied volatility, investment, employment, and lobbying are defined as before. $PRisk_{i,t}$, *Textbook-based* $PRisk_{i,t}$, and *Unweighted* $PRisk_{i,t}$ are standardized by their respective standard deviations. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 12: Horse-race between $PRisk_{i,t}$ and firm-level EPU

PANEL A: VOLATILITY REGRESSIONS	Realized volatility $_{i,t}$ (standardized)		Implied volatility $_{i,t}$ (standardized)	
	(1)	(2)	(3)	(4)
Firm level EPU $_{i,t}$ (1)	0.026** (0.010)	0.016 (0.010)	0.019 (0.013)	0.006 (0.013)
PRisk $_{i,t}$ (standardized)		0.019*** (0.004)		0.025*** (0.005)
N	162,153	162,153	115,059	115,059
PANEL B: CORPORATE OUTCOMES	$I_{i,t}/K_{i,t-1} * 100$		$\Delta emp_{i,t}/emp_{i,t-1} * 100$	
	(1)	(2)	(3)	(4)
Firm level EPU $_{i,t}$ (1)	-0.303*** (0.114)	-0.230** (0.115)	-2.577*** (0.672)	-1.921*** (0.692)
PRisk $_{i,t}$ (standardized)		-0.148*** (0.042)		-0.681*** (0.159)
N	119,853	119,853	45,930	45,930
Time FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes

Notes: Firm level EPU $_{i,t}$ (1) is a dummy variable equal to one if the transcript has at least one of the word combinations specified in Baker, Bloom, and Davis (2016). $PRisk_{i,t}$, realized and implied volatility, investment, and employment are defined as before. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 13: PRisk_{*i,t*} and PRisk10K_{*i,t*})

PANEL A	Realized volatility _{<i>i,t</i>} (standardized)		Implied volatility _{<i>i,t</i>} (standardized)	
	(1)	(2)	(3)	(4)
PRisk _{<i>i,t</i>} (standardized)	0.025*** (0.006)		0.038*** (0.008)	
PRisk10K _{<i>i,t</i>} (standardized)		0.012* (0.006)		0.020** (0.008)
<i>R</i> ²	0.395	0.399	0.471	0.491
<i>N</i>	44,039	36,871	31,307	26,627
PANEL B	$\frac{I_{i,t}}{K_{i,t-1}} * 100$		$\frac{\Delta emp_{i,t}}{emp_{i,t-1}} * 100$	
	(1)	(2)	(3)	(4)
PRisk _{<i>i,t</i>} (standardized)	-0.792*** (0.216)		-0.769*** (0.155)	
PRisk10K _{<i>i,t</i>} (standardized)		-0.321 (0.250)		0.000 (0.189)
<i>R</i> ²	0.037	0.036	0.024	0.024
<i>N</i>	42,958	33,535	45,930	36,715
PANEL C	Log(1+\$ lobby _{<i>i,t</i>})		Log(1+\$ donations _{<i>i,t</i>})	
	(1)	(2)	(3)	(4)
PRisk _{<i>i,t</i>} (standardized)	0.286*** (0.037)		0.135*** (0.027)	
PRisk10K _{<i>i,t</i>} (standardized)		0.291*** (0.053)		0.212*** (0.042)
<i>R</i> ²	0.264	0.314	0.249	0.332
<i>N</i>	48,679	38,038	48,679	38,038
PANEL D	# of recipients _{<i>i,t</i>}		Hedge _{<i>i,t</i>}	
	(1)	(2)	(3)	(4)
PRisk _{<i>i,t</i>} (standardized)	0.617*** (0.144)		0.010*** (0.002)	
PRisk10K _{<i>i,t</i>} (standardized)		1.028*** (0.211)		0.013*** (0.002)
<i>R</i> ²	0.157	0.209	0.195	0.245
<i>N</i>	48,679	38,038	48,679	38,038

Notes: This table shows regressions at the firm-year level. PRisk_{*i,t*} is our standard measure of political risk; PRisk10K_{*i,t*} is calculated as PRisk_{*i,t*} but on the MD&A section of the company's 10K report. All other variables are defined as in the preceding tables. Each regression specification controls for the log of firm assets, as well as time and sector fixed effects. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 14: Firm-level political risk and firm actions: Alternative definitions of sectors

	2-digit SIC			3-digit SIC		4-digit SIC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\frac{I_{i,t}}{K_{i,t-1}} * 100$	-0.162*** (0.043)	-0.159*** (0.042)	-0.188*** (0.039)	-0.182*** (0.045)	-0.179*** (0.043)	-0.205*** (0.048)	-0.188*** (0.045)
$\frac{\Delta \text{capex}_{i,t}}{\text{capex}_{i,t-1}} * 100$	-0.347*** (0.121)	-0.391*** (0.124)	-0.337** (0.141)	-0.427*** (0.155)	-0.346* (0.181)	-0.517*** (0.169)	-0.373* (0.195)
$\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$	-0.806*** (0.149)	-0.725*** (0.156)	-0.772*** (0.188)	-0.810*** (0.164)	-0.774*** (0.197)	-0.846*** (0.170)	-0.762*** (0.201)
Sector FE	no	yes	implied	yes	implied	yes	implied
Time FE	no	yes	yes	yes	yes	yes	yes
Sector*time FE	no	yes	yes	yes	yes	yes	yes
Firm FE	no	no	yes	no	yes	no	yes
# of sectors	65			258		407	
<i>Variance decomposition</i>							
Firm-level variation	91.69%			82.93%		78.33%	
Permanent differences across firms within sector (Firm FE)	19.87%			17.52%		16.82%	
Variation over time in identity of firms within sector most affected (residual)	71.82%			65.41%		61.51%	

Notes: This table shows results from regressions of the variable indicated in the most left column on $PRisk_{it}$ using different industry classifications — 2-digit (columns 2-3), 3-digit (columns 4-5), and 4-digit SIC (columns 6-7) — as fixed effects. Capital investment, capital expenditure guidance, and net hiring are defined as in Table 5. In all regressions, $PRisk_{i,t}$ is standardized by its standard deviation. All specifications control for the log of firm assets. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively. The lower panel of the table shows tabulations of the R^2 from a projection of $PRisk_{i,t}$ on various sets of fixed effects.

Appendix Table 15: Specifications of Table 10 using other firm-level outcomes

	(1)	(2)	(3)	(4)	(5)
PANEL A					
	$\frac{I_{i,t}}{K_{i,t-1}} * 100$				
PRisk _{<i>i,t</i>} (standardized)	-0.159*** (0.042)	-0.181*** (0.043)	-0.167*** (0.044)	-0.153*** (0.042)	-0.155*** (0.042)
R ²	0.076	0.078	0.078	0.076	0.076
N	119,853	113,169	110,313	119,853	119,853
PANEL B					
	$\frac{\Delta \text{capex}_{i,t}}{\text{capex}_{i,t-1}} * 100$				
PRisk _{<i>i,t</i>} (standardized)	-0.391*** (0.124)	-0.405*** (0.125)	-0.435*** (0.126)	-0.389*** (0.124)	-0.391*** (0.124)
R ²	0.183	0.187	0.189	0.183	0.183
N	22,520	21,738	21,136	22,520	22,520
PANEL C					
	$\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$				
PRisk _{<i>i,t</i>} (standardized)	-0.725*** (0.156)	-0.619*** (0.163)	-0.725*** (0.156)	-0.660*** (0.156)	-0.662*** (0.157)
R ²	0.056	0.057	0.056	0.058	0.058
N	45,930	43,312	45,930	45,930	45,930
PANEL D					
	Log(1+\$ donations _{<i>i,t+1</i>})				
PRisk _{<i>i,t</i>} (standardized)	0.086*** (0.018)	0.093*** (0.019)	0.096*** (0.019)	0.070*** (0.018)	0.070*** (0.018)
R ²	0.264	0.281	0.288	0.292	0.292
N	176,173	166,923	161,581	176,173	176,173
PANEL E					
	# of recipients _{<i>i,t+1</i>}				
PRisk _{<i>i,t</i>} (standardized)	0.468*** (0.120)	0.495*** (0.127)	0.506*** (0.131)	0.413*** (0.114)	0.411*** (0.114)
R ²	0.163	0.174	0.182	0.182	0.182
N	176,173	166,923	161,581	176,173	176,173
PANEL F					
	Hedge _{<i>i,t+1</i>}				
PRisk _{<i>i,t</i>} (standardized)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
R ²	0.160	0.171	0.174	0.176	0.176
N	176,173	166,923	161,581	176,173	176,173
PANEL G					
	Log(1+\$ lobby _{<i>i,t+1</i>})				
PRisk _{<i>i,t</i>} (standardized)	0.184*** (0.028)	0.196*** (0.029)	0.207*** (0.029)	0.159*** (0.026)	0.159*** (0.026)
R ²	0.282	0.295	0.300	0.317	0.317
N	147,228	139,004	133,994	147,228	147,228
Time FE	yes	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes	yes
Sector × time FE	yes	yes	yes	yes	yes

Notes: This table is similar to Table 10; it shows results of the same panel regressions, but instead of using realized and implied volatility as outcome, we use the outcome specified above the respective panel. We only report the coefficient of $PRisk_{i,t}$. All remaining variables and regression specifications are defined as in Table 10 (for example, all specifications control for the log of firm assets). Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 16: Dispersion of firm-level political risk

	Standard deviation of residual				
	(1)	(2)	(3)	(4)	(5)
Mean of $PRisk_{i,t}$ (standardized)	0.790*** (0.056)		0.875*** (0.057)	0.843*** (0.080)	0.820*** (0.054)
Real GDP growth $_t$ (% change)		-2.804* (1.670)	2.789*** (0.829)		
R^2	0.777	0.046	0.814	0.656	0.808
N	60	60	60	60	58

This table reports estimates from OLS regressions using the standard deviation of the residual from a projection of $PRisk_{i,t}$ (standardized) on firm, time, and sector \times time fixed effects, calculated by quarter, as dependent variable. Column 1 corresponds to the data plotted in Figure 5. Column 2 uses real GDP growth $_t$ (% change) instead of the mean of $PRisk_{i,t}$. Column 3 adds both. Column 4 replicates column 1 but restricts the data to firms with non-missing data at least 58 of the 60 quarters. Column 5 replicates column 1 and controls for EPU beta (2-year rolling) $_{i,t} \times$ mean of $PRisk_{i,t}$ when projecting $PRisk_{i,t}$ on the set of fixed effects. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Appendix Table 17: Mapping of political topics to topics given by OnTheIssues.org

Political topic	OnTheIssues.org topics
Economic Policy & Budget	Budget & Economy; Jobs; Corporations
Environment	Energy & Oil; Environment
Trade	Free Trade
Institutions & Political Process	Government Reform
Health	Health Care
Security & Defense	Homeland Security; War & Peace
Tax Policy	Tax Reform
Technology & Infrastructure	Technology & Infrastructure
	Not used: Abortion; Civil Rights; Crime; Drugs; Education; Families & Children; Foreign Policy; Gun Control; Immigration; Principles & Values; Social Security; Welfare & Poverty

Appendix Table 18: Timing of associations between lobbying and topic-specific political risk

	$\mathbb{1}[\text{lobbying}_{i,t+1}^T > 0] * 100)$		
	(1)	(2)	(3)
$\text{PRisk}_{i,t}^T$ (standardized)	0.098*** (0.030)		0.081*** (0.030)
$\text{PRisk}_{i,t+1}^T$ (standardized)	0.069** (0.032)	0.072** (0.032)	0.064** (0.030)
$\text{PRisk}_{i,t+2}^T$ (standardized)		0.051 (0.031)	0.048 (0.031)
Time FE	yes	yes	yes
Sector FE	implied	implied	implied
Topic FE	yes	yes	yes
Firm FE	yes	yes	yes
Firm*topic FE	yes	yes	yes
Number of firms	5962	5626	5626
Number of periods	36	35	35
Number of topics	8	8	8
R^2	0.702	0.721	0.721
N	860,504	791,568	791,568

This table shows the results from a regression of $\mathbb{1}[\text{lobbying}_{i,t+1}^T > 0] * 100)$ on two leads of $\text{PRisk}_{i,t}^T$. $\text{PRisk}_{i,t}^T$ is standardized by its standard deviation. Lobbying is semi-annual for all pre-2008 quarters; the quarters for which there is no lobby expense are excluded from the regression. All specifications control for the log of firm assets. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.