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 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.

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From the UK's vote to leave the European Union to repeated shutdowns of the US 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 earnings 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 matters. 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 conversations 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 political 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 our counts.

A key challenge to any 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.[1] 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

[1] Berger et al. (2017) argue measured uncertainty in aggregate US data tends to increase when the economy is affected by adverse shocks.

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 results, 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 measured 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 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, sector $\times$ time, and firm fixed effects, or if we increase the granularity of our definition of sectors. The data thus strongly suggest the 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 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 political risk that resulted purely from politicians' inability to compromise in a timely fashion. We find that a one-standard-deviation increase in a firm's political risk generated by 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.[2]

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). 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).[3] Relative to this existing work, we provide not just the first firm-level measure of political risk—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 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).

In contrast, our findings suggest political actions may affect the activity of firms in ways that are

[2]A growing literature argues that managers' expectations affect firm actions, even when they are biased (Gennaioli and Shleifer, 2018).

[3]Jurado 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.

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) (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).[4] We contribute to this literature by showing that firms may lobby and cultivate connections to politicians in an attempt to actively manage political risk. Consistent with these results, Akey and Lewellen (2016) show that firms whose stock returns are most sensitive to variation in EPU are more likely to donate to politicians.[5]

Finally, several recent studies 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 (e.g., 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.[6] In addition, whereas prior studies have relied on newspaper archives and corporate disclosures as source texts (Baker et al. (2016); Koijen et al. (2016); Li et al. (2013); 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. We also build on Loughran and McDonald (2011) who use sentiment analysis of corporate documents to predict market outcomes (see Loughran and McDonald (2016) for a survey).

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.[7] During our sample window, firms commonly host

[4]Also see Johnson and Mitton (2003); Khwaja and Mian (2005); Leuz and Oberholzer-Gee (2006); Snowberg et al. (2007); Ferguson and Voth (2008); and Acemoglu et al. (2016, 2018). In turn, politicians reciprocate by distributing favors in the form of bailouts, reduced oversight, or by allocating government contracts (Faccio et al., 2006; Goldman et al., 2009; Benmelech and Moskowitz, 2010; Correia, 2014; Tahoun, 2014; Tahoun and van Lent, 2019).

[5]A 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.

[6]Alternative 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)).

[7]The majority of calls are held within 33 days of the new quarter. The exception is the first quarter, where the median call is on the 45th day of the quarter. This delay is due to the fact that the first-quarter call is typically held after the

one earnings call every fiscal quarter, thus generating roughly four observations per firm per year. 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.[8]

We obtain each firm's total expenditure on lobbying US Congress in each quarter from the Center for Responsive Politics (CRP). The same source also gives a list of 80 possible topics that each firm lobbied on. We manually match between these 80 topics and the eight topics our topic-based measure of political risk encompasses (see Appendix Table I for details).

We obtain additional data from the following sources: campaign contributions by Political Action Committees (PACs) from the CRP website, data on government contracts from USAspending.gov, stock information from the Center for Research in Security Prices, firm-quarter-level implied volatility from OptionMetrics, and—for a smaller set of sample firms—data on projected capital expenditure for the following fiscal year from I/B/E/S Guidance. Finally, 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. Table I provides summary statistics and Appendix A gives details on the construction of all variables.

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 matters. 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 conference call participants and firm management that centers on risks associated with political matters. Clearly, any issue that is raised during an earnings call will tend to be of some concern either for the firm's

annual report (i.e., Form 10-K) is made public, which goes with longer statutory due dates and is more labor intensive.

[8] In untabulated analysis, we find the average number of words spoken in our sample conference calls is 7,533. Matsumoto et al. (2011) find a typical earnings call lasts for about 46 minutes, with on average 18 minutes for the managerial presentation and 28 minutes for the Q&A.

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.

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).[9] We then similarly decompose each conference-call transcript of firm i in quarter t into a list of bigrams contained in the transcript $b = 1, ..., B_{it}$.[10] 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:

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

where $1[\bullet]$ is the indicator function, $\mathbb{P} \backslash \mathbb{N}$ 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

[9] Previous 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).

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

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 $1[b \in \mathbb{P}\backslash\mathbb{N}] \times f_{b,\mathbb{P}}/B_{\mathbb{P}}$ 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(# of training libraries/# 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 to account for the length of the transcript. In robustness checks reported below, we experiment with a 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, 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 (i.e., combining pattern-based sequence classification with conditional word-counts) is that it also lends itself to measuring the extent of conversations about issues that are related to political risk, but logically distinct from it, simply by modifying the conditioning information in (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,

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

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 $\mathbb{N}\backslash\mathbb{P}$ rather than $\mathbb{P}\backslash\mathbb{N}$ 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:

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

where $S(c)$ is a function that assigns a value of $+1$ if bigram c is associated with positive sentiment (using Loughran and McDonald (2011)'s sentiment dictionary), a value of -1 if bigram c is associated with negative sentiment, and 0 otherwise. Frequently used positive and negative words include 'good,' 'strong,' 'great,' and 'loss,' 'decline,' and 'difficult,' respectively.[11,12] (See Appendix Table II for details.) Using the same procedure we also calculate a measure of overall sentiment

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

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

2.3 Training libraries

$PRisk_{it}$ 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

[11] We 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.

[12] One 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.

financial indicators. 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 political versus non-political topics.

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 edition; 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.

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 libraries, yielding 101,165 bigrams in the set $\mathbb{P}\backslash\mathbb{N}$. 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 their mean is equal to the mean of the bigrams identified using only the textbook-based libraries.[13] See Appendix B for details.

Finally, we obtain the list of synonyms for "risk," "risky," "uncertain," and "uncertainty" from the Oxford dictionary (shown in Appendix Table III). 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."

[13] Because 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.

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 II shows the bigrams in $\mathbb{P}\backslash\mathbb{N}$ 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 I 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}.

Table III 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 but one 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 one false positive is shown in Panel B: a call held by Piedmont Natural Gas that, in fact, does not contain a discussion of risks associated with politics. 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 $\mathbb{P}\backslash\mathbb{N}$, does not relate to political risk.

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.[14]

On two other occasions, as column 5 shows, the conditioning on proximity to synonyms produces

[14] As an additional validation exercise we also manually read excerpts of hundreds of transcripts to verify the information content of $PRisk_{it}$ at various points of its distribution. See Appendix C for details.

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 I plots the average across firms of our measure of overall political risk at each point in time, $1/N \sum_i PRisk_{it}$, and compares it with the newspaper-based measure of economic policy uncertainty (EPU) constructed by Baker et al. (2016). 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.[15] 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, and thus increase and decrease aggregate political risk at regular intervals. Figure II 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.

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' and 'construction' sectors on average spend the highest proportion of their time discussing risks associated with political topics, whereas firms in the 'retail trade' sector have the lowest average $PRisk_{it}$ (see Appendix Figure III). These means line up intuitively with parts of the economy that may be considered most dependent on government for regulation or expenditure. Figure III 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

[15] For comparison, Appendix Figure II plots the average across firms of our measure of non-political risk ($NPRisk_{it}$), which comfortingly 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 I.

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 IV 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.[16] 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).[17]

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 cluster standard errors by firm.[18]

Panel A of Table IV 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 some of this association is driven by the time-series dimension: when adding the mean of $PRisk_{i,t}$ across firms at each point in time as a control, the coefficient of interest drops to 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

[16] Using business 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).

[17] For 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 6.15×0.028=0.172 and 6.40×0.140=0.896.

[18] To corroborate our choice of standard errors, Appendix Figure IV shows the results of a falsification exercise, where we repeatedly assign $PRisk_{it}$ 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 V shows alternative standard errors clustered by sector and time.

build up to our standard specification by adding time and sector fixed effects. Doing so reduces the size of the coefficient of interest, but it remains 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 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 return 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 volatile 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 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 return 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)).[19] Second, a large literature in

[19] In macroeconomic models, increases in aggregate risk may increase or decrease aggregate investment, because of general equilibrium effects on the interest rate (see, e.g., Fernández-Villaverde et al. (2015); Hassan and Mertens (2017)). However,

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 V 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, $\Delta\text{capexg}_{i,t}/\text{capexg}_{i,t-1}$, as the change (relative to the previous quarter) in the firm's guidance for total capital expenditure for the next fiscal year. Net hiring, $\Delta\text{emp}_{i,t}/\text{emp}_{i,t-1}$, is the change in year-to-year employment over last year's value.[20,21] All specifications are in the same form as (5), always including time and sector fixed effects, as well as controlling for the log of the firm's assets. The coefficients in columns 1 to 3 suggest 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.[22,23]

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 document a negative relation between their measure of aggregate economic policy uncertainty and firm-level investment rates and employment growth. 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.

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 relative increases in firm-level risk should always decrease its investment relative to other firms.

[20]Because these data on investment, capital expenditure, and employment are notoriously noisy, we winsorize each of these variables at the first and last percentile.

[21]Here the number of observations is smaller because employment data are at the annual frequency. In all specifications at the annual frequency, we take an arithmetic mean of $PRisk_{it}$ across all transcripts of a given firm and year.

[22]Because 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.

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

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.[24] 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, 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, 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 V shows that, indeed, predominantly larger firms donate to politicians in the face of political risk, whereas smaller firms tend to react with more vigorous retrenchment of employment and investment (the latter statistically significant only at the 10% level).[25]

Mean versus 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 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,

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

[25]This latter result is also 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.

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 VII and VIII). 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 IX shows additional validation exercises.

The primary concern with our interpretation of the results in Table V 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 $PRisk_{it}$ and $PSentiment_{it}$ is negative (-0.08), so that news about higher political risk tends to arrive when sentiment about politics is negative. Nevertheless, Table VI shows no evidence of omitted variable bias in our estimates. Columns 1 and 5 replicate our standard specification. Columns 2 and 6 show 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 may 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.[26] 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

[26] Consistent 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).

managers' incentives to blame political risks for bad performances affect our results.[27]

Taken together, these results bolster our confidence that $PRisk_{it}$ correctly identifies variation in the second moment (risk), rather than 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 VII. 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 (-0.255, s.e.=0.043), whereas the one on $PRisk$ falls in absolute terms but retains its negative sign and statistical significance (-0.085, s.e.=0.042).[28] The same pattern, albeit with a much smaller change in the size of the coefficient on $PRisk_{it}$, holds for employment growth (column 5), suggesting both $PRisk_{it}$ and $NPRisk_{it}$ 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 including $Risk_{it}$ again 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 versus Panels B and C) as strongly supportive of our interpretation that $PRisk_{it}$ indeed captures 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

[27]Consistent with these results, Appendix Tables X and XI show that interactions between $PRisk_{it}$ and $PSentiment_{it}$, $Sentiment_{it}$, and prior stock returns are never statistically distinguishable from zero when added to these specifications.

[28]Since 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.

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 US listed firms, 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 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 XII). Appendix Table XIII 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 $\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}$ 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).[30] 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 XIII and XIV.

[29]Another, completely different, approach would be to manually select passages of transcripts that focus on risks associated with political matters, 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 training sample.

[30]Specifically, 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."

For use in robustness checks below, we also constructed an implementation of $PRisk_{it}$ using the 'Management Discussion and Analysis' (MD&A) section of firms' annual Form 10-K filings as an alternative text source. Appendix Table VI 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 disclosures in 10-Ks are highly scripted and tend to have higher disclosure thresholds than earnings conference calls (Hollander et al., 2010; Brown and Tucker, 2011; Cohen et al., 2018).

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 US listed firms and establish new stylized facts.

A notable feature of the associations between $PRisk_{it}$ and corporate outcomes, as documented in Tables IV and V, is that they all hold even when we condition on time and sector 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 VIII, is that time fixed effects—and thus the time-series variation of aggregate political risk shown in Figure I—account 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. Most of the variation in measured political risk (91.69%) thus 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.[31]

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

[31] However, 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.

for the remainder (i.e., the remaining 71.82% not explained by time or firm fixed effects).[32] These conclusions do not change substantially when we use more granular sector definitions in columns 2 and 3 of Table VIII.[33]

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 assignment of political risk across firms within a given sector changes dramatically over time. Thus, when facing political risk, firms may be considerably more concerned about their position in this 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).[34]

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, the highly significant associations between $PRisk_{it}$ and corporate outcomes, as documented in Tables IV and V, strongly suggest this variation nevertheless has economic content. In Figure IV, 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 drop all fixed effects (panel a) and when we supplement our standard specification with the interaction of sector and time fixed effects (panel b), as well as as fixed effects for each firm-sector pair (panel c).[35] For example, the unconditional correlation between $PRisk_{it}$ and the investment rate is -0.162 (s.e.=0.043) in panel (a) and -0.188 (s.e.=0.039) in panel (c). (As before, this pattern is largely invariant to using more granular definitions of sectors; see Appendix Table XV.) 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.

Appendix D shows a range of estimates of the degree of measurement error contained in different

[32]This 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).

[33]Of 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 $PRisk_{it}$.

[34]Consistent with this interpretation, Akey and Lewellen (2016) also find little persistence in firms' "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.

[35]The fact that there is no attenuation in the coefficient when we condition on granular variation implies that the quantitative results from our variance decomposition in Table VIII also extend to the explained variation of our regressions: if we regress the firm's investment rate separately on the sector-time and the firm-level components of $PRisk_{it}$, we find that the latter accounts for 87.2% of the total variation explained by $PRisk_{it}$. Repeating this calculation for employment growth and planned capital expenditure yields shares of 64.2% and 99.4%, respectively (see Appendix Table XVI for details).

dimensions of $PRisk_{it}$. Consistent with the patterns in Figure IV, we find that the share of firm-level variation accounted for by measurement error is only about 10% higher than in the overall variation.

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 $PRisk_{it}$ on its quarterly mean across firms, and then include the interaction of this political risk beta with the mean of $PRisk_{it}$ across firms in our analysis of variance. Specifically, we include it as a control in addition to the full set of time, sector, and sector $\times$ time fixed effects. We find this interaction (not shown) accounts for less than a hundredth of the firm-level variation in overall political risk, suggesting $PRisk_{it}$ is not well described by a model in which firms have stable heterogenous exposures to aggregate political risk.

Consistent with this result, column 2 of Table IX shows the association between $PRisk_{it}$ and stock return volatility remains almost unchanged when we control for such heterogenous exposure to aggregate political risk. Column 3 allows for time variation of firms' political risk beta on a two-year rolling window. 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 that any information reflected in these alternative measures is subsumed in $PRisk_{it}$. The following columns repeat the same procedure but construct each firm's political risk beta by regressing its daily stock return on daily variation in EPU_t (columns 4 and 5). Columns 6 and 7 instead use the log of one plus the dollar amount the firm has outstanding in government contracts as a measure of exposure to aggregate political risk. In each case, the inclusion of these variables has no effect on the coefficient of interest. Appendix Table XVII shows the same result for all other corporate outcomes studied in Table V.

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 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 increases 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 the economy 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 results also suggest that firm-level political risk may directly lower aggregate total factor productivity. If firms respond to political risk by reducing hiring and investment, and if exposure to political risk varies across firms, then it directly affects the allocation of capital and labor across firms. If some or all of this firm-level variation in political risk is inefficient — say attributable to political or administrative dysfunction rather than prudent regulation — then it indirectly causes a misallocation of productive resources across firms, which in turn lowers the productive capacity of the economy and total factor productivity (Hsieh and Klenow, 2009; Arayavechkit et al., 2017). Appendix E makes this argument formally.

Our results thus suggest that the effectiveness of political decision-making may have important macroeconomic effects not only by affecting aggregate political risk, but also by affecting the dispersion of firm-level political risk over time.

To probe this possibility, we project $PRisk_{it}$ on the interaction of time and sector fixed effects and plot the cross-sectional standard deviation of the residual at each point in time in the top panel of Figure V to show how the (cross-sectional) dispersion of firm-level political risk evolved over time. For comparison, the figure also plots the average across firms of $PRisk_{it}$. The figure shows the dispersion of firm-level political risk tends to be higher during the 2008-9 recession. 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 standard deviation of the residuals on the mean of $PRisk_{it}$ yields a coefficient of 0.989 (s.e.=0.0672), implying a one-percentage-point increase in aggregate political risk is associated with a 0.99-percentage-point increase in the cross-sectional standard deviation of firm-level political risk.[36]

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 V 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 0.96 of the standard deviation of the full panel), and that it is positively skewed, with a fat right tail.

4.2 Case studies: two firms

As a useful illustration of the kind of firm-level political risk captured by our measure, Figure VI 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.[37] 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

[36] As is already apparent from visual inspection, Appendix Table XVIII shows that this association remains significant, and even dominates, when we simultaneously control for the business cycle.

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

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.

The example firm in panel B is a smaller high-tech firm, specializing in voice-over-IP systems. As is evident from Figure VI, 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 points. 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 $\mathbb{Z} = \{\mathbb{P}_1, ..., \mathbb{P}_Z\}$, 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 before, 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:

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

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 $1[b \in \mathbb{P} \backslash \mathbb{N}] \times 1[|b-r| < 10] > 0$. 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, $log(Z/f_{b,\mathbb{Z}})$, 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 exclusively in discussion of topic T.

To implement (6), we rely on the collection of newspaper articles, speeches, press releases, 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 language. 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."[38]

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 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.

Validation. Appendix Table XX shows the top 15 bigrams most indicative of each of our eight political topics: the bigrams with the highest $\frac{f_{b,\mathbb{P}_T}}{B_{\mathbb{P}_T}} log(Z/f_{b,\mathbb{Z}})$. For example, the top 15 bigrams associated with "economic policy & budget" include "balanced budget," "legislation provides," and "bankruptcy bill;" those associated with "security & defense" include "on terror," "from iraq," and "nuclear weapons." 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. For example, 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 apparent false positives when considering only the text surrounding the highest-scoring bigrams shown in the table: i.e., the

[38] Appendix Table XIX gives details on the mapping between the materials provided on the website and these topics.

transcripts of Landry's restaurants, Medcath Corp., Piedmont Natural Gas, and HMS Holdings Corp. However, a closer reading of these transcripts reveals the surrounding paragraphs do in fact contain significant discussions of political risks associated with the possibility of new tax and minimum wage legislation in Texas, the prospect of congressional action on extending the moratorium on specialized hospitals, the regulation of coal emissions, and the lobbying activities of the firm at the state level, respectively. Indeed, while the top bigram of Medcath picks up the SEC-required safe harbor statement, its CEO has the following response to an analyst's query: "This is politics, so anything can happen." We find only one false positive among the 24 top transcripts listed in Appendix Table XX (the February 2012 transcript by Yandex, in the "Technology and infrastructure" category).

Lobbying by topic. For each firm-quarter, the CRP lists which of 80 possible topics a given firm lobbies on. Using our mapping between these 80 topics and our eight political topics (Appendix Table I), 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 this lobbying activity to our topic-based measures of political risk takes the form:

$$\mathbb{1}[Lobbying^T_{i,t+1} > 0] * 100 = \delta_t + \delta_i + \delta_T + \theta PRisk^T_{it} + \gamma^T X_{it} + \epsilon^T_{it}, \tag{7}$$

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 $PSentiment_{it}$. The θ coefficient measures the association between a firm's political risk associated with a given topic and its propensity to lobby on that topic.

Panel A of Table X shows estimates of θ, where column 3 corresponds directly to (7). The coefficient estimate (0.794, s.e.=0.047) implies that 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 sample firms lobby on any given topic, this effect corresponds to a 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 on each topic they 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.[39]

[39] Going one step further, Appendix Figure probes the heterogeneity of this effect across topics by allowing the θ

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 θ coefficient in (7) 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 a confounding 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 XXI replicates column 5 of Table X—our most demanding specification relating lagged $PRisk_{it}^{T}$ to lobbying at $t+1$—while adding both contemporaneous and future $PRisk^{T}$ to the regression. 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,[40] and the fact that the three point estimates are not dramatically different from each other.

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 rule it out 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.

coefficient in (7) to vary by topic.

[40] A 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). Lobbying by topic exhibits similarly high persistence (0.882, s.e.=0.005).

Although we have no such natural experiments available, we can nevertheless speak to this issue by making use of three historical case studies that allow us to trace jumps in political risk directly to specific political crises. 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 political risk that resulted purely from the inability of politicians to reach 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 identify firms most concerned with these episodes.

We show the use of these terms is concentrated among firms that derive a higher share of their revenue from the government and is associated with significant increases in our measure of political risk associated with the topic "economic policy & budget." Using the frequency of use of these terms within a given transcript as an instrument for the firm's political risk associated with "economic policy & budget," we estimate a local average treatment effect, where a one-standard-deviation increase in political risk associated with this topic results in a 2.430-percentage point increase (s.e.=0.937) in the probability that the firm lobbies the government on the same topic in the following quarter. See Appendix F for details on these results.

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. 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 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. Moreover, these correlations with firm actions remain unchanged when we control for news about the mean of the firm's political and non-political shocks, lending us confidence that our measure of political risk genuinely captures information about the second moment, not the first moment.

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 by 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.

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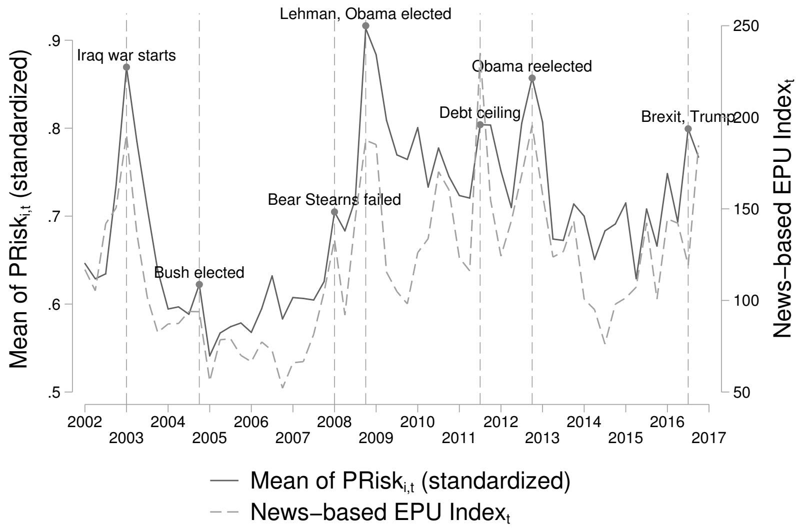
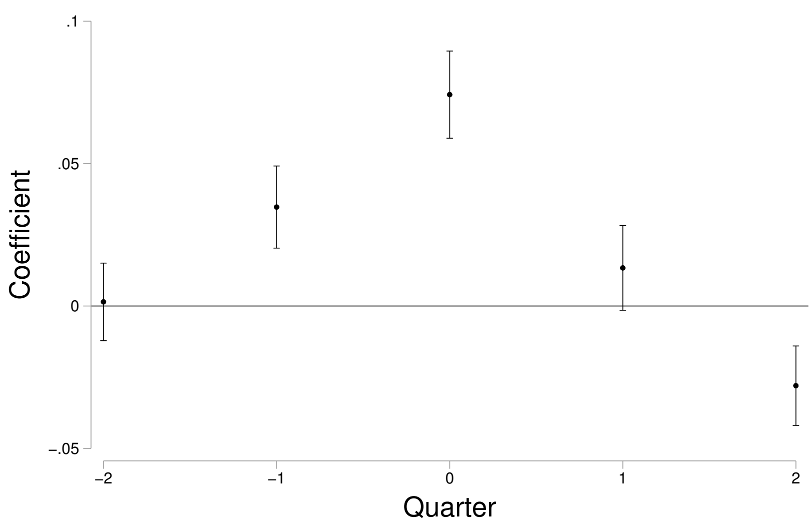
Figure I: Variation in $PRisk_{i,t}$ over time and correlation with EPU



Notes: This figure shows the time-average of $PRisk_{i,t}$ (standardized by its standard deviation in the time series) across firms in each quarter together with the news-based Economic Policy Uncertainty (EPU) 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. The Pearson correlation between the time-average of $PRisk_{i,t}$ with the Chicago Board Options Volatility Index (CBOE VIX) is 0.608 with a p-value of 0.000.

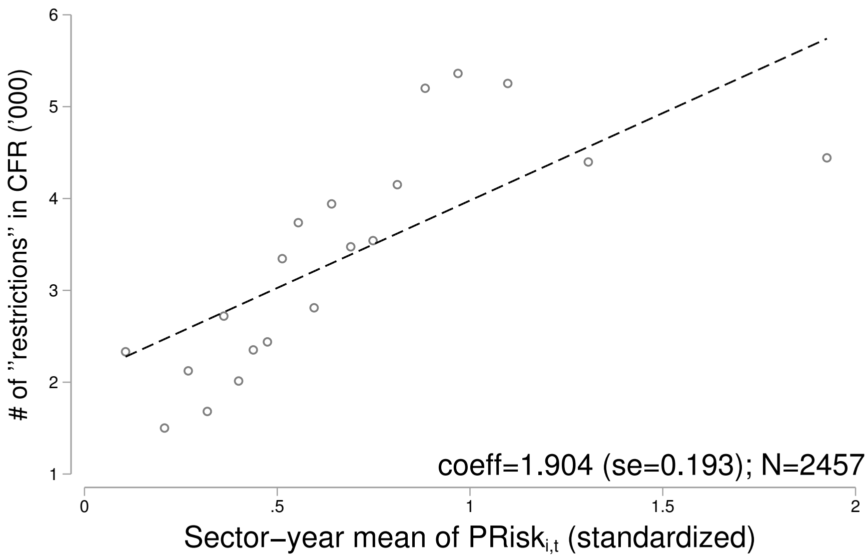
Figure II: Variation in $PRisk_{i,t}$ around federal elections



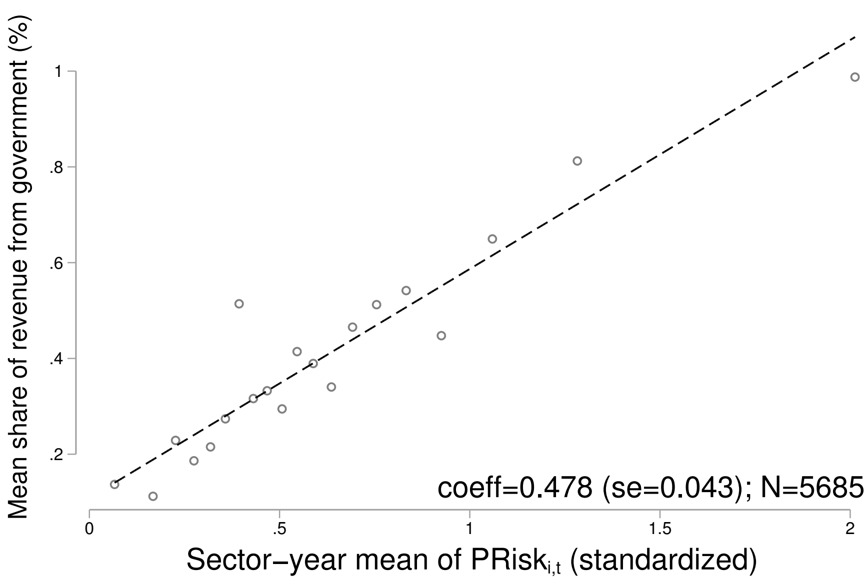
Notes: This figure plots the coefficients and 95% confidence intervals from a regression of $PRisk_{i,t}$ (standardized) on dummy variables indicating quarters with federal (i.e., presidential and congressional) elections, as well as two leads and lags. The specification also controls for firm fixed 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 III: $PRisk_{i,t}$ and sector exposure to politics

Panel A: Index of regulatory constraints

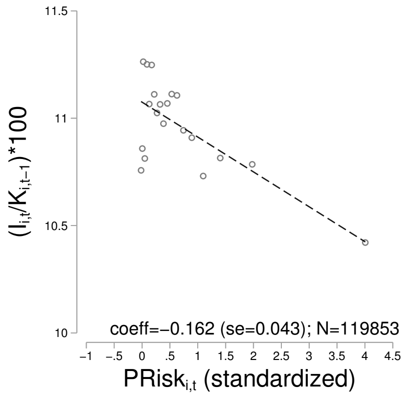


Panel B: Share of revenue from federal government

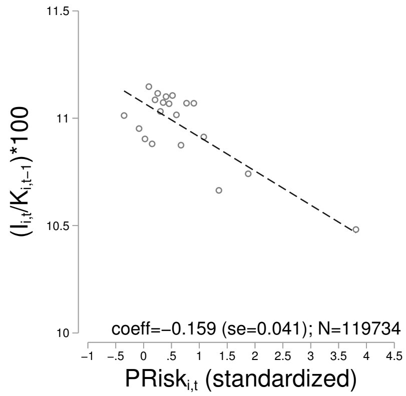


Notes: This figure shows binned scatterplots of the relationship between the sector-year average of $PRisk_{i,t}$ (standardized) and two different measures of sector exposure to politics. In Panels A and B the number of industries is 211 and 413, respectively. In Panel A, the index of regulatory constraints 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 IX) divided by total net sales. $PRisk_{i,t}$ is standardized by its standard deviation.

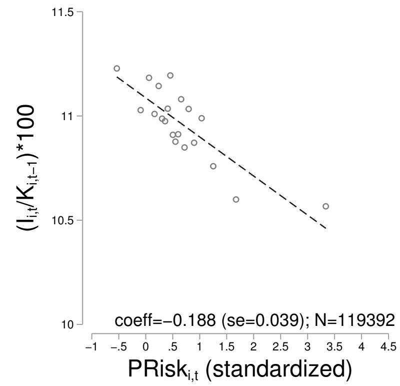
Figure IV: Associations between $PRisk_{i,t}$ and corporate actions



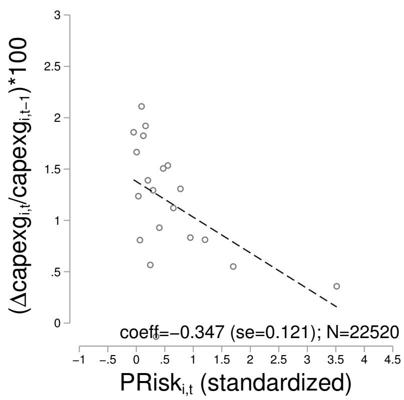
(a) No FE



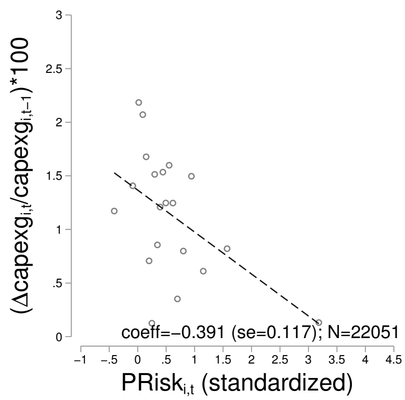
(b) Sector×time FE



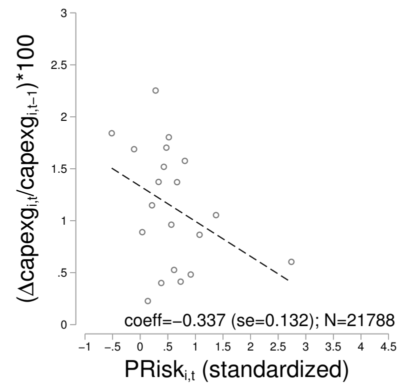
(c) Adding firm FE



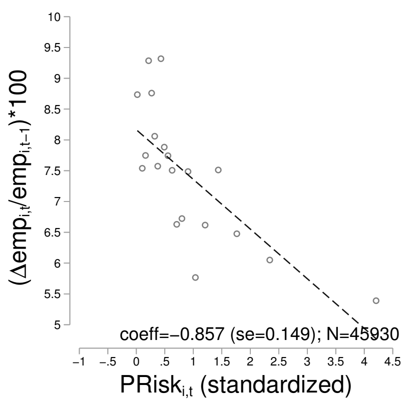
(d) No FE



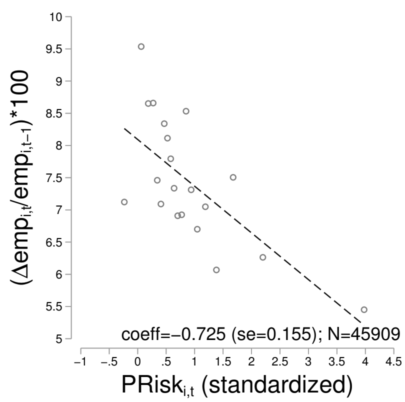
(e) Sector×time FE



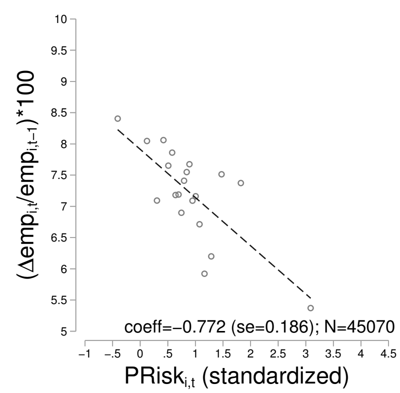
(f) Adding firm FE



(g) No FE



(h) Sector×time FE

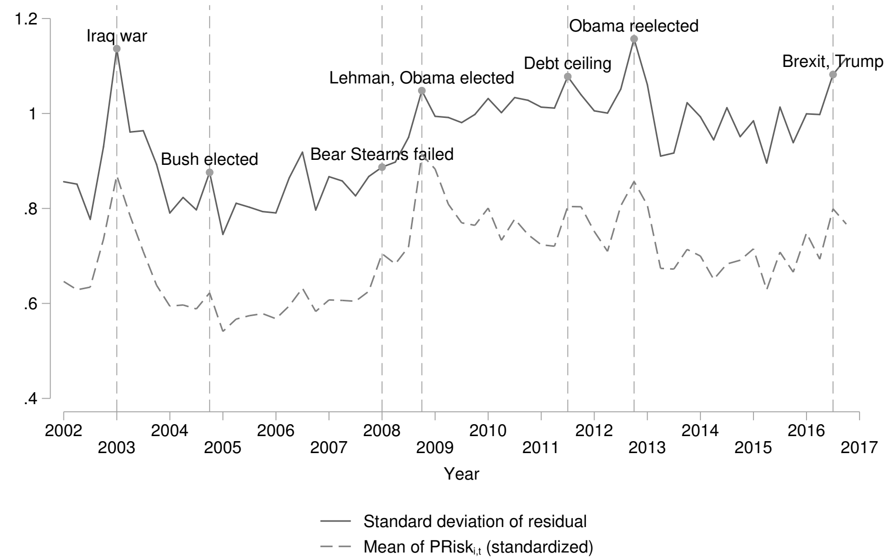


(i) Adding firm FE

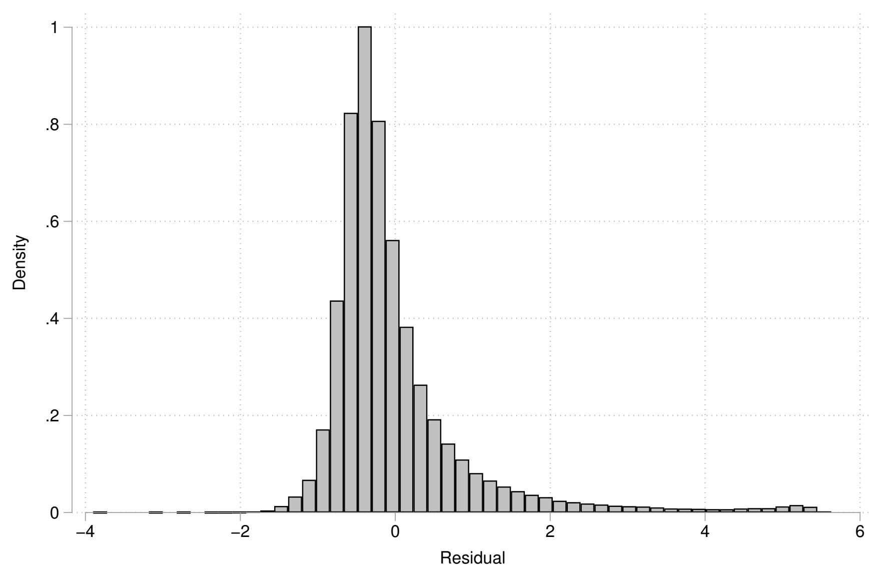
Notes: This figure shows nine panels of binned added-variable plots for $PRisk_{i,t}$ (standardized). Going from top to bottom, the panels are for investment, $I_{i,t}/K_{i,t-1} * 100$, (Panels a, b, and c), capex guidance, $\Delta \text{capexg}_{i,t}/\text{capeg}_{i,t-1} * 100$, (Panels d, e, and f), and employment, $\Delta \text{emp}_{i,t}/\text{emp}_{i,t-1} * 100$, (Panels g, h, and i). The left-hand panels show the relations without fixed effects, the middle panels control for sector, time, and sector×time interactions, and the right-hand panels control, in addition, for firm fixed effects (thus controlling simultaneously for time, sector, firm and sector× time fixed effects). All specifications control for the log of firm assets. $PRisk_{i,t}$ is standardized by its standard deviation.

Figure V: Dispersion of firm-level political risk

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



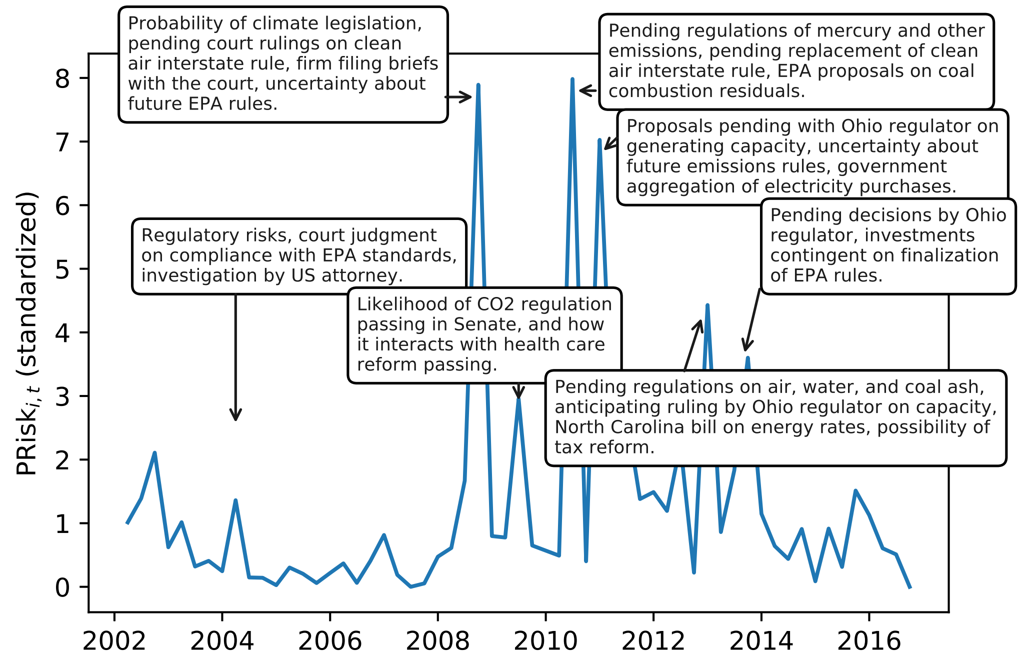
(b) Panel B: Distribution of the residual of $PRisk_{i,t}$



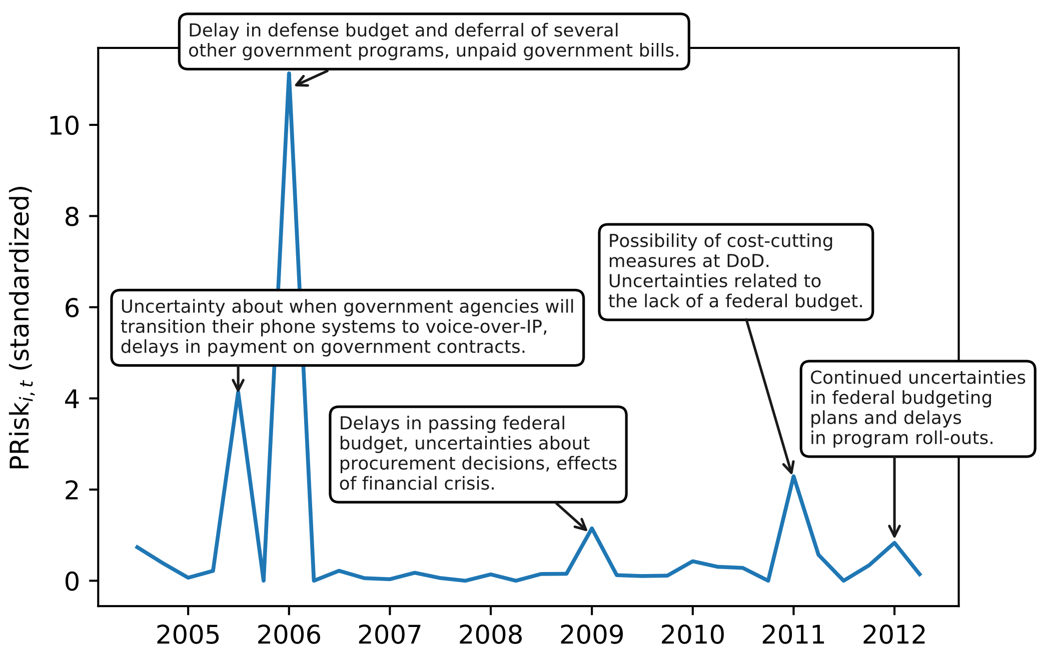
Notes: Panel A plots the mean of $PRisk_{i,t}$ (standardized) and the cross-sectional standard deviation at each point in time of the residual from a projection of $PRisk_{i,t}$ (standardized) on sector fixed effects, time fixed effects, and the interaction of time and SIC2-digit sector fixed effects. 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 VI: 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. Panel A shows $PRisk_{i,t}$ of a large energy generation company that heavily invested in coal-burning furnaces of an older generation. 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.

Table I: Summary statistics

Panel A: Firm-quarter	Mean	Median	St. Dev.	Min	Max	N
PRisk$_{i,t}$ (standardized)	0.70	0.37	1.00	0.00	6.08	176,173
PSentiment$_{i,t}$ (standardized)	0.90	0.85	1.00	-2.13	3.96	176,173
Assets$_{i,t}$ (millions)	15,271	1,217	97,502	0.13	3,069,706	173,887
Realized volatility$_{i,t}$ (standardized)	1.52	1.27	1.00	0.21	8.31	162,153
Implied volatility$_{i,t}$ (standardized)	2.05	1.82	1.00	0.46	6.31	115,059
Earnings announcement surprise$_{i,t}$	-0.01	0.00	1.43	-235.83	301.81	161,403
Stock return 7 days prior to earnings call$_{i,t}$	0.00	0.00	0.02	-0.24	0.40	148,196
$I_{i,t}/K_{i,t-1}$	0.11	0.09	0.11	-0.03	1.07	119,853
Δcapexg$_{i,t}$/capexg$_{i,t-1}$	0.01	0.00	0.16	-0.44	0.87	22,520
Δsales$_{i,t}$/sales$_{i,t-1}$	0.05	0.02	0.35	-0.98	3.46	173,887
Lobby expense$_{i,t}$ (thousands)	80.08	0.00	381.08	0.00	15,460.00	147,228
Donation expense$_{i,t}$ (thousands)	5.13	0.00	27.71	0.00	924.50	176,173
# of recipients$_{i,t}$	2.73	0.00	14.01	0.00	521.00	176,173
Hedge$_{i,t}$	0.06	0.00	0.24	0.00	1.00	176,173
Federal contracts$_{i,t}$ (thousands)	3,516	0.00	49,488	0.00	3,841,392	162,124
PRisk Economic Policy & Budget$_{i,t}$ (standardized)	0.48	0.22	1.00	0.00	64.75	176,173
PRisk Environment$_{i,t}$ (standardized)	0.33	0.13	1.00	0.00	88.78	176,173
PRisk Trade$_{i,t}$ (standardized)	0.30	0.10	1.00	0.00	164.55	176,173
PRisk Institutions & Political Process$_{i,t}$ (standardized)	0.39	0.16	1.00	0.00	71.69	176,173
PRisk Health$_{i,t}$ (standardized)	0.27	0.10	1.00	0.00	73.02	176,173
PRisk Security & Defense$_{i,t}$ (standardized)	0.42	0.19	1.00	0.00	123.42	176,173
PRisk Tax Policy$_{i,t}$ (standardized)	0.37	0.15	1.00	0.00	97.37	176,173
PRisk Technology & Infrastructure$_{i,t}$ (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$_{i,t}$ (standardized)	0.90	0.59	1.00	0.00	5.97	48,679
PSentiment$_{i,t}$ (standardized)	1.09	1.05	1.00	-1.90	4.07	48,679
Δemp$_{i,t}$/emp$_{i,t-1}$	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$^T_{i,t}$ (standardized)	0.61	0.27	1.00	0.00	6.34	1,177,824
Lobby$^T_{i,t}$ ($\mathbb{1}$)	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, $PRisk^T_{i,t}$ 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 at the first and last percentile. 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$_{i,t}$ is 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 at the first and last percentile. Capex guidance, Δcapexg$_{i,t}$/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 and winsorize the resulting variable at the first and last percentile. Δsales$_{i,t}$/sales$_{i,t-1}$ is the change in quarter-to-quarter sales over last quarter's value, winsorized at the first and last percentile. Lobby expense$_{i,t}$ is the total lobby expense during quarter t by firm i. Donation expense$_{i,t}$ is 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, Δemp$_{i,t}$/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, $PRisk^T_{i,t}$, where T = {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 II: 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 column reports the number of occurrences of the bigram across all transcripts.

Table III: 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 ($f_{b,\mathbb{P}}/B_{\mathbb{P}}$)
NEVADA GOLD CASINOS INC	10-Sep-2008	51.94	– 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	48.70	– exposure of insurance portfolio to political risk in Spain, Portugal, Greece, Ukraine, and Kazakhstan.	accident year ratios the combined ratios we have talked about **the political** —RISK— business particularly really shouldnt be looked at on a
Female Health	10-Feb-2009	44.17	– 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.	market acceptance the economic and business environment and the impact **of government pressures** currency —RISKS— capacity efficiency and supply **constraints and** other
Employers Holdings Inc	01-May-2014	43.81	– 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
National Mentor Holdings, Inc.	12-Feb-2010	42.55	– 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**
Applied Energetics, Inc.	11-May-2009	41.12	– collaboration with Pentagon to develop technology to counter IED/roadside bombs; – funding of weapons programs.	of products and the —UNCERTAINTY— of the timing **and magnitude of government funding and** customer orders **dependence on** sales **to government** customers
Calian Group Ltd	09-Feb-2011	41.05	– 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
Insurance Australia Group Ltd	23-Feb-2012	38.70	– 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
FPIC Insurance Group, Inc.	30-Oct-2008	38.69	– impact of the composition of Congress on the likelihood of tort reform; – Florida state politics.	a —CHANCE— for national **tort reform and** i dont see **the constitution of** congress **changing in** such a way after **this election**
BANKFINANCIAL CORP	4-Nov-2008	38.33	– TARP and CPP programs; – developments in Freddie Mac; – consequences of a change in administration and party in power.	was **an accurate** metaphor and really given all the —UNCERTAINTIES— **of government involvement** in operations and business activities and given the capital

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 $b \in \mathbb{P}\backslash\mathbb{N}$ 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 III: Transcript excerpts with highest $PRisk_{i,t}$: Panel B

Firm name	Call date	$PRisk_{i,t}$ (standardized)	Discussion of political risks associated with:	Text surrounding bigram with highest weight ($f_{b,\mathbb{P}}/B_{\mathbb{P}}$)
Nanogen, Inc.	8-Aug-2007	37.20	– FDA approval of company products.	**a dip** in revenues during q related to the —UNCERTAINTY— **of government approval for** the phase **funding of** the cdc contract additionally
World Acceptance Corporation	25-Jul-2006	36.90	– impact of legislation in Texas and other states.	management analyst i wanted to followup on the regulatory **front the states** that you had **mentioned the** —POSSIBILITY— of some positive **legislation**
United Refining Company	23-Jul-2010	35.32	– effect of government tax refund on bottom line; – state funding of infrastructure projects and the associated demand for asphalt products.	shape on asphalt **the funding is** very —IFFY— in all **the states so** and the private work is very slow operator operator
Magellan Health Services	29-Jul-2010	35.26	– actions of state Medicaid administrators and insurance regulators; – state procurement of healthcare reform and federal regulations; – state gubernatorial elections; – Affordable Care Act.	future so this is a time of quite —UNCERTAINTY— for **the states** they are not **sure what** the fmap will be if
Piraeus Bank SA	19-Mar-2015	34.45	– political situation in Greece; – consequences of elections on bank deposits; – relations between EU and Greece, politics of Greece leaving the Euro zone.	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	9-Jun-2009	34.39	—	**your point** as you will recall in all three of **the states** that we have serve jim we are —EXPOSED— only to
Platinum Underwriters Holdings Ltd	18-Feb-2010	33.21	– politics and government decision-making in Kazakhstan and Ukraine; – China's ability to fulfill lending commitments.	we have had historically had a very small participation in **the political** —RISK— market backing only a couple of players **parties that**
Transcontinental Inc.	14-Sep-2006	31.81	– tax reform in Quebec.	magazines when you look at exports that we do to **the states no** —DOUBT— that is affecting the top and the bottom
Hemisphere Media Group Inc	12-Aug-2014	31.70	– restructuring of government debt in Puerto Rico.	i think largely a result of the —UNCERTAINTY— regarding restructuring **of government** debt and the general overhang on **the weak economy in**
Pointer Telocation Ltd	30-May-2012	31.27	– political conditions in Israel.	anticipated such —RISKS— and —UNCERTAINTIES— include **a dependence on** economic **and political conditions in israel the** impact of competition supply constraints as

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 $b \in \mathbb{P}\backslash\mathbb{N}$ 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 IV: Validation: Implied and realized volatility

PANEL A	Implied volatility$_{i,t}$ (standardized)					
	(1)	(2)	(3)	(4)	(5)	(6)
PRisk$_{i,t}$ (standardized)	0.056***	0.034***	0.033***	0.025***	0.013***	0.016**
	(0.006)	(0.006)	(0.006)	(0.005)	(0.003)	(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***	0.023***	0.020***	0.020***	0.014***	0.013**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.002)	(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	n/a	n/a
Firm FE	no	no	no	no	yes	yes
CEO FE	no	no	no	no	no	yes

Notes: This table shows the results from 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 at the first and last percentile. Implied volatility$_{i,t}$ is for 90-day at-the-money options of firm i and time t and is also winsorized at the first and last percentile. $PRisk_{i,t}$ is our measure for firm-level political risk. 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 V: 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)
$\text{PRisk}_{i,t}$ (standardized)	–0.159***	–0.338***	–0.769***	–0.075
	(0.041)	(0.120)	(0.155)	(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+$ $\text{donations}_{i,t+1}$)	# of $\text{recipients}_{i,t+1}$	$\text{Hedge}_{i,t+1}$	Log(1+$ $\text{lobby}_{i,t+1}$)
	(1)	(2)	(3)	(4)
$\text{PRisk}_{i,t}$ (standardized)	0.087***	0.462***	0.007***	0.186***
	(0.018)	(0.118)	(0.001)	(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+$ $\text{donations}_{i,t+1}$)	Log(1+$ $\text{lobby}_{i,t+1}$)
	(1)	(2)	(3)	(4)
$\text{PRisk}_{i,t}$ (standardized)	–0.223***	–1.064***	0.025	0.168***
	(0.059)	(0.230)	(0.016)	(0.032)
$\text{PRisk}_{i,t} \times \mathbb{1}\{\text{assets}_{i,t} > \text{median assets}\}$	0.149*	0.620**	0.154***	0.085
	(0.081)	(0.289)	(0.039)	(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. 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, net hiring, capital expenditure guidance, and net sales are all winsorized at the first and last percentile. Panel B shows the results of regressions of lobbying and donation activity by firms on $PRisk_{i,t}$. Log(1+$ $\text{donations}_{i,t+1}$) (column 1) is the log of one plus the sum of all contributions paid to federal candidates; # of $\text{recipients}_{i,t+1}$ (column 2) is defined as the number of recipients of donations; $\text{Hedge}_{i,t+1}$ (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+$ $\text{lobby}_{i,t+1}$) (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 VI: Mean vs. variance of political shocks

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)	(7)	(8)
$\text{PRisk}_{i,t}$ (standardized)	–0.159***	–0.145***	–0.120***	–0.157***	–0.769***	–0.683***	–0.534***	–0.622***
	(0.041)	(0.041)	(0.041)	(0.046)	(0.155)	(0.156)	(0.156)	(0.163)
$\text{PSentiment}_{i,t}$ (standardized)		0.216***				1.181***		
		(0.043)				(0.155)		
$\text{Sentiment}_{i,t}$ (standardized)			0.454***				2.252***	
			(0.048)				(0.161)	
Mean stock return 7 days $\text{prior}_{i,t}$ (%)				0.025				0.319*
				(0.022)				(0.166)
Earnings announcement $\text{surprise}_{i,t}$				0.058*				0.024***
				(0.032)				(0.005)
R^2	0.035	0.035	0.036	0.037	0.024	0.026	0.029	0.026
N	119,853	119,853	119,853	100,661	45,930	45,930	45,930	41,327
Panel B	Log(1+$ $\text{lobby}_{i,t+1}$)				Log(1+$ $\text{donations}_{i,t+1}$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{PRisk}_{i,t}$ (standardized)	0.186***	0.199***	0.204***	0.217***	0.087***	0.094***	0.097***	0.100***
	(0.027)	(0.027)	(0.027)	(0.031)	(0.018)	(0.018)	(0.018)	(0.020)
$\text{PSentiment}_{i,t}$ (standardized)		0.203***				0.117***		
		(0.032)				(0.022)		
$\text{Sentiment}_{i,t}$ (standardized)			0.203***				0.115***	
			(0.037)				(0.026)	
Mean stock return 7 days $\text{prior}_{i,t}$ (%)				0.028***				0.012***
				(0.007)				(0.004)
Earnings announcement $\text{surprise}_{i,t}$				–0.007				–0.003
				(0.007)				(0.004)
R^2	0.268	0.269	0.269	0.291	0.250	0.251	0.251	0.282
N	147,228	147,228	147,228	121,650	176,173	176,173	176,173	147,521
Panel C	# of $\text{recipients}_{i,t+1}$				$\text{Hedge}_{i,t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{PRisk}_{i,t}$ (standardized)	0.462***	0.491***	0.509***	0.512***	0.007***	0.007***	0.007***	0.008***
	(0.118)	(0.121)	(0.121)	(0.136)	(0.001)	(0.001)	(0.001)	(0.001)
$\text{PSentiment}_{i,t}$ (standardized)		0.474***				0.008***		
		(0.100)				(0.001)		
$\text{Sentiment}_{i,t}$ (standardized)			0.541***				0.007***	
			(0.131)				(0.002)	
Mean stock return 7 days $\text{prior}_{i,t}$ (%)				0.032**				0.001**
				(0.013)				(0.000)
Earnings announcement $\text{surprise}_{i,t}$				0.011				–0.000
				(0.013)				(0.000)
R^2	0.147	0.148	0.149	0.172	0.140	0.141	0.141	0.158
N	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 $\text{Sentiment}_{i,t}$ are standardized by their standard deviation. Mean stock return 7 days $\text{prior}_{i,t}$ (%) is the average stock return for the 7 days prior to the earnings call of firm i at date t. Earnings announcement $\text{surprise}_{i,t}$ is defined as $(\text{EPS}_{i,t} - \text{EPS}_{i,t-4})/\text{price}_{i,t}$, where $\text{EPS}_{i,t}$ is earnings per share (basic) of firm i at time t, and $\text{price}_{i,t}$ 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 VII: Falsification exercise: Political risk, non-political risk, and overall risk

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)
$\text{PRisk}_{i,t}$ (standardized)	–0.145***	–0.085**	–0.075*	–0.683***	–0.441***	–0.402**
	(0.041)	(0.042)	(0.045)	(0.156)	(0.162)	(0.182)
$\text{NPRisk}_{i,t}$ (standardized)		–0.255***			–0.854***	
		(0.043)			(0.166)	
$\text{Risk}_{i,t}$ (standardized)			–0.136**			–0.509**
			(0.059)			(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+\$ $\text{lobby}_{i,t+1}$)			Log(1+\$ $\text{donations}_{i,t+1}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{PRisk}_{i,t}$ (standardized)	0.199***	0.204***	0.212***	0.094***	0.095***	0.108***
	(0.027)	(0.027)	(0.028)	(0.018)	(0.018)	(0.019)
$\text{NPRisk}_{i,t}$ (standardized)		–0.023			–0.004	
		(0.022)			(0.015)	
$\text{Risk}_{i,t}$ (standardized)			–0.025			–0.025
			(0.037)			(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 $\text{recipients}_{i,t+1}$			$\text{Hedge}_{i,t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{PRisk}_{i,t}$ (standardized)	0.491***	0.502***	0.439***	0.007***	0.008***	0.007***
	(0.121)	(0.121)	(0.108)	(0.001)	(0.001)	(0.001)
$\text{NPRisk}_{i,t}$ (standardized)		–0.042			–0.001	
		(0.052)			(0.001)	
$\text{Risk}_{i,t}$ (standardized)			0.098			0.001
			(0.101)			(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 explores $PRisk_{it}$'s logical components. $NPRisk_{i,t}$ (non-political risk) is calculated in the same way as as $PRisk_{i,t}$, but based on non-political bigrams instead of political bigrams. $Risk_{i,t}$ counts the number of synonyms of "risk," "risky," "uncertain," or "uncertainty" irrespective of whether they are near a political bigram. As with $PRisk_{i,t}$, all measures are relative to the transcript length. The dependent 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 VIII: Variance decomposition of $PRisk_{it}$

	(1)	(2)	(3)
Sector granularity	2-digit SIC	3-digit SIC	4-digit SIC
Time FE	0.81%	0.81%	0.81%
Sector FE	4.38%	6.31%	6.87%
Sector × 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 the 3-digit and 4-digit SIC level, respectively. The "firm-level" variation at the annual frequency is 89.47%, 82.12%, and 78.38% at the 2-digit, 3-digit, and 4-digit SIC level, respectively.

Table IX: 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***	0.026***	0.026***	0.027***	0.027***	0.029***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
β_i × mean of PRisk$_{i,t}$ (std.)		0.001					
		(0.003)					
$\beta_{i,t}$ (2-year rolling) × mean of PRisk$_{i,t}$ (std.)			–0.000				
			(0.000)				
EPU beta$_i$ × mean of PRisk$_{i,t}$ (std.)				0.414			
				(4.764)			
EPU beta (2-year rolling)$_{i,t}$ × mean of PRisk$_{i,t}$ (std.)					0.017		
					(0.063)		
Log(1+$ federal contracts$_{i,t}$)						–0.013***	–0.006
						(0.001)	(0.005)
Log(1+$ federal contracts$_{i,t}$) × 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***	0.019***	0.020***	0.020***	0.020***	0.021***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
β_i × mean of PRisk$_{i,t}$ (std.)		–0.000					
		(0.000)					
$\beta_{i,t}$ (2-year rolling) × mean of PRisk$_{i,t}$ (std.)			0.000				
			(0.000)				
EPU beta$_i$ × mean of PRisk$_{i,t}$ (std.)				9.464***			
				(1.276)			
EPU beta (2-year rolling)$_{i,t}$ × mean of PRisk$_{i,t}$ (std.)					–0.163***		
					(0.014)		
Log(1+$ federal contracts$_{i,t}$)						–0.010***	0.003
						(0.001)	(0.004)
Log(1+$ federal contracts$_{i,t}$) × 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×time FE	yes	yes	yes	yes	yes	yes	yes

Notes: This table is similar to Table IV. It shows results of regressions with realized and implied volatility as the dependent variable in Panels A and B, respectively. β_i is constructed for each firm by regressing $PRisk_{it}$ on its quarterly mean across firms. EPU beta$_i$ is an alternative firm-specific beta obtained from a regression of the firm's daily stock returns on Baker, Bloom, and Davis' (2016) daily Economic Policy Uncertainty (EPU) Index; rolling betas are constructed by running these regressions using observations only from the 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 (standardized by its standard deviation in the time series); 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. The dependent variables are defined as in Table IV. Standard errors are clustered at the firm level. ***, **, and * denote statistical significance at the 1, 5, and 10% level, respectively.

Table X: 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***	1.050***	0.794***	0.819***	0.114***
	(0.094)	(0.093)	(0.047)	(0.048)	(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***	0.133***	0.098***	0.101***	0.015***
	(0.013)	(0.013)	(0.006)	(0.006)	(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	n/a	n/a	n/a
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 equals 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. Because 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. $PRisk_{i,t}^{T}$ 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.