FIRM-LEVEL POLITICAL RISK: MEASUREMENT AND EFFECTS*

Tarek A. Hassan
Stephan Hollander
Laurence van Lent
Ahmed Tahoun

We adapt simple tools from computational linguistics to construct a new measure of political risk faced by individual U.S. firms: the share of their quarterly earnings conference calls that they devote to political risks. We validate our measure by showing that 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 captured neither by the interaction of sector and time fixed effects nor by heterogeneous exposure of individual firms to aggregate political

*We thank seminar participants at Barcelona GSE, Boston University, the Philadelphia Fed, Frankfurt School of Finance and Management, University of Bristol, Universidad Carlos III de Madrid, University of Chicago, University of Exeter, Humboldt University, Lancaster University, London Business School, Mannheim University, University of Melbourne, MIT (Department of Economics), MIT Sloan, University of Southern California, Stanford SITE, the Stigler Center, DAR Conference at the University of Maastricht, the BFI-Hoover Conference on Policymaking and Uncertainty, the Western Finance Association, the NBER Summer Institute, and the NBER EFG meeting. We received helpful feedback from Scott Baker, Nick Bloom, Steve Davis, Gene Fama, Tom Ferguson, Alex Frankel, Ray Fisman, Mariassunta Giannetti, Igor Goncharov, Lars Peter Hansen, Rick Hornbeck, Emir Kamenica, Larry Katz, Ties de Kok, Christian Leuz, Juhani Linnainmaa, Valeri Nikolaev, Lubos Pastor, Andrei Shleifer, Chad Syverson, Stephen Terry, Pietro Veronesi, Luigi Zingales, and four anonymous referees. We are most grateful to Menno van Zaanen for generously providing his textual analysis code and for advising on computational linguistics matters. Markus Schwedeler deserves a special thanks for his excellent research assistance. We also thank Jakub Dudzic, Chris Emmery, Yusiyu Wang, and Hongcen Wei for their help as research assistants at various stages. Funding for this project was provided by the Institute for New Economic Thinking and by the Deutsche Forschungsgemeinschaft-Project-ID 403041268 - TRR 266. We further gratefully acknowledge the Fama-Miller Center at the University of Chicago (Hassan) and the London Business School (Tahoun) for financial support.

The Quarterly Journal of Economics (2020), 2135–2202. doi:10.1093/qje/qjz021.

risk. The dispersion of this firm-level political risk increases significantly at times with high aggregate political risk. Decomposing our measure of political risk by topic, we find that firms that devote more time to discussing risks associated with a given political topic tend to increase lobbying on that topic, but not on other topics, in the following quarter. *JEL Codes:* D8, E22, E24, E32, E6, G18, G32, G38, H32.

I. Introduction

From the United Kingdom's vote to leave the European Union to repeated shutdowns of the U.S. 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 article, 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 U.S. 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, Raghavan, and Schütze 2008) to distinguish between language associated with political versus nonpolitical 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 U.S. politics and articles from the political section of U.S. newspapers) and a training library of nonpolitical text (i.e., an accounting textbook, articles from nonpolitical sections of U.S. newspapers, and transcripts of conversations on nonpolitical 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 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 nonpolitical 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—for example, "the constitution," "public opinion," and "the FAA."

Second, we find that 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, Bloom, and Davis (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 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, Bond, and Van Reenen 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 way 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 to 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 the algorithm to count the same political bigrams as used before but condition on their use in conjunction with positive and negative tone words, rather than synonyms for risk or uncertainty. We find that this measure of political sentiment has all expected properties. For example, it correctly identifies transcripts with positive and negative news about politics, and more positive political sentiment is associated with higher stock returns, investment, and hiring. Nevertheless, controlling for political sentiment (and other measures of the mean of the firm's prospects) has no effect on the main results, lending us confidence that our measure of political risk captures information about the second moment but not the first one.

Using a similar approach, we construct measures of nonpolitical risk (conditioning on nonpolitical 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.

1. Berger, Dew-Becker, and Giglio (2017) argue measured uncertainty in aggregate U.S. data tends to increase when the economy is affected by adverse shocks.

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 U.S. 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 × 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 × time, and firm fixed effects or if we increase the granularity of our definition of sectors. The data thus strongly suggest that 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 that 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, Bloom, and Davis 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 just 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 1 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 that 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 U.S. 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 create a mapping between specific political topics discussed in conference calls and the topics that are the object of the 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 an 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 that the persistence of these associations conditional on time, firm, sector × time, and (in the case of lobbying) topic and topic × 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 but 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 Barack Obama's 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 (std. err. = 0.937) in the probability that the firm lobbies the government on the the topic of "economic policy and 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, although showing statistically and economically significant associations between firm-level variation in our measures and firm actions, we do not claim that 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, Gala, and Li 2013; Gourio, Siemer, and Verdelhan 2015; Handley and Limão 2015; Kelly, Pástor, and Veronesi 2016; Koijen, Philipson, and Uhlig 2016; Besley and Mueller 2017; Mueller, Tahbaz-Salehi, and Vedolin 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 U.S. aggregate economic

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

policy uncertainty (EPU) based on textual analysis of newspaper articles developed by Baker, Bloom, and Davis (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 publications, 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, Nguyen, and Schmid 2012; Pastor and Veronesi 2012, 2013; Born and Pfeifer 2014; Fernandez-Villaverde, Garicano, and Santos 2013; Drautzburg, Fernandez-Villaverde, and Guerron-Quintana 2017).

In contrast, our findings suggest that political actions may affect the activity of firms in ways that are not well reflected in representative-agent models. For example, an increase in the dispersion of firm-level political risk may interact with financial or other frictions to reduce growth (Gilchrist, Sim, and Zakrajšek 2014; Arellano, Bai, and Kehoe 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, Saffie, and Shin 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

3. Jurado, Ludvigson, and Ng (2015), Bachmann, Elstner, and Sims (2013), and Giglio, Kelly, and Pruitt (2016) propose measures of aggregate (political and nonpolitical) uncertainty in the U.S. economy.

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

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 predefined dictionaries of significant words to process source documents (e.g., Baker, Bloom, and Davis 2016). By contrast, our approach aims to endogenously capture 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 (Gentzkow and Shapiro 2010; Li, Lundholm, and Minnis 2013; Baker, Bloom, and Davis 2016; Koijen, Philipson, and Uhlig 2016), 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).

II. 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 one earnings call every fiscal quarter, thus generating roughly

5. A large literature documents that lobbying is pervasive in the U.S. political system (Milyo, Primo, and Groseclose 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 because the first-quarter call is typically held after the

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 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 8 topics our topic-based measure of political risk encompasses (see Online 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 Poor's Compustat. Table I provides summary statistics, and Online Appendix A gives details on the construction of all variables.

III. 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 argue

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, Pronk, and Roelofsen (2011) find a typical earnings call lasts about 46 minutes, with an average of 18 minutes for the managerial presentation and 28 minutes for the Q&A.

TABLE I

SUMMARY STATISTICS

	Mean	Median	St. dev.	Min	Max	N
Panel A: Firm-quarter						
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

TABLE I

(CONTINUED)

	Mean	Median	St. dev.	Min	Max	N
Panel B: Firm-year						
$\text{PRisk}_{i,t}$ (standardized)	0.90	0.59	1.00	0.00	5.97	48,679
$\text{PSentiment}_{i,t}$ (standardized)	1.09	1.05	1.00	–1.90	4.07	48,679
$\Delta\text{emp}_{i,t}/\text{emp}_{i,t-1}$	0.07	0.03	0.30	–0.78	2.50	45,930
Panel C: Firm-topic-quarter						
$\text{PRisk}^{T}_{i,t}$ (standardized)	0.61	0.27	1.00	0.00	6.34	1,177,824
$\text{Lobby}^{T}_{i,t}$ ($\mathbb{1}$)	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 nonmissing 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 seven days prior to the earnings call at date t. Earnings announcement surprise$_{i,t}$ is defined as $\frac{\text{EPS}_{i,t}-\text{EPS}_{i,t-4}}{\text{price}_{i,t}}$, 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. Capital investment, $\frac{I_{i,t}}{K_{i,t-1}}$, 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, $\frac{\Delta\text{capexg}_{i,t}}{\text{capexg}_{i,t-1}}$, 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 and winsorize the resulting variable at the first and last percentile. $\frac{\Delta\text{sales}_{i,t}}{\text{sales}_{i,t-1}}$ 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 1 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, $\frac{\Delta\text{emp}_{i,t}}{\text{emp}_{i,t-1}}$, 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.

that this measure can be interpreted as a proxy for the political risk and uncertainty individual firms face.

III.A. Defining a Measure of Political Risk

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

Rather than a priori deciding on specific words associated with different topics, we distinguish political from nonpolitical topics using a pattern-based sequence-classification method developed in computational linguistics (Song and Wu 2008; Manning, Raghavan, and Schütze 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 nonpolitical text, archetypical of the discussion of nonpolitical topics, $\mathbb{N}$. Each training library is the set of all adjacent two-word combinations (bigrams) contained in the respective political and nonpolitical 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 count the number of occurrences of bigrams indicating discussion of a given political topic within the set of 10 words surrounding a

9. Previous research suggests text-classification results generally improve by applying n-grams (usually bigrams) of words as opposed to single words (unigrams) (Tan, Wang, and Lee 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 preprocessing procedures, such as removing stop words and lemmatizing. However, we found these procedures did not substantially affect our results.

synonym for "risk" or "uncertainty" on either side, and divide by the total number of bigrams in the transcript:

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

where $\mathbb{1}[\bullet]$ 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 nonpolitical 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 nonpolitical) text 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 $\mathbb{1}[b \in \mathbb{P} \backslash \mathbb{N}] \times \frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}$ 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, equation (1) is a straightforward 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 equation (1). Across all of these variations, we generally find that 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 that our results are similar when we do not use this weighting.)

III.B. 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 equation (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 equation (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,

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

where $\mathbb{R}$ denotes the same set of synonyms for risk or uncertainty used in the construction of equation (1). Similarly, we measure the share of the conversations centering on risks and uncertainties associated with nonpolitical topics, $NPRisk_{it}$, by counting and weighting $\mathbb{N}\backslash\mathbb{P}$ rather than $\mathbb{P}\backslash\mathbb{N}$ in equation (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 that 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 nonpolitical bigrams, now conditioning on proximity to positive and negative words, rather than synonyms of risk or uncertainty:

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

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] (See Online Appendix Table II for details.) Using the same procedure, we also calculate a measure of overall sentiment

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

as well as a measure of nonpolitical sentiment ($NPSentiment_{it}$), constructed by counting and weighting $\mathbb{N}\backslash\mathbb{P}$ rather than $\mathbb{P}\backslash\mathbb{N}$ in equation (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 Online Appendix and refer to it in the main text only when relevant.

III.C. 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 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 judgment we have to make is about training libraries—what text may be considered archetypical of discussions of political versus nonpolitical topics.

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. 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 we chose not to complicate the construction of our measures by explicitly allowing for it.

In our applications, we show results using three alternative approaches to defining the political and nonpolitical libraries ($\mathbb{P}$ and $\mathbb{N}$). In the first, we use undergraduate textbooks, where the nonpolitical library consists of bigrams extracted from a textbook on financial accounting (Libby, Libby, and Short 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 (2013).

In the second, we construct the nonpolitical 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 we 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 include all bigrams from the Santa Barbara Corpus of Spoken American English (Du Bois et al. 2000) as part of the nonpolitical 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 show that 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 $\left(\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}\right)$ such that their mean is equal to the mean of the bigrams identified using only the textbook-based libraries.[12] See Online Appendix B for details.

12. 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.

Finally, we obtain the list of synonyms for "risk," "risky," "uncertain," and "uncertainty" from the Oxford English Dictionary (shown in Online 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., call moderators asking for the next question), and "venture."

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 standardize with its sample standard deviation.

III.D. Validation

We next describe the output of our measure and verify that 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, $\left(\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}\right)$, that is, the bigrams associated most strongly with discussion of political versus nonpolitical 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." Online Appendix Figure I shows a histogram of these bigrams by their term frequency. It shows that 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 contain significant discussions of risk associated with political topics. For example, the transcript with the highest score (Nevada Gold Casino Inc in September 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 Environmental Protection Agency. Other transcripts focus on uncertainty surrounding tort reform, government funding, legislation, and many other political topics.

The one false positive is shown in Table III, 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 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,

TABLE II

Top 120 Political Bigrams Used in Construction of $PRisk_{i,t}$

Bigram	$\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \times 10^5$	Frequency	Bigram	$\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \times 10^5$	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	1,091	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

TABLE II
(CONTINUED)

Bigram	$\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \times 10^5$	Frequency	Bigram	$\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}} \times 10^5$	Frequency
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 $\left(\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}\right)$ 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.

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 $\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}$ (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.[13]

On two other occasions, as Table III, column (5) shows, the conditioning on proximity to synonyms produces apparently false

13. 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 Online Appendix C for details.

TABLE III

TRANSCRIPT EXCERPTS WITH HIGHEST $PRisk_{i,t}$

Firm name	Call date	$PRisk_{i,t}$ (standardized)	Discussion of political risks associated with:	Text surrounding bigram with highest weight $\left(\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}\right)$
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' compensation.	of —HAZARD— **groups but** as you start moving it around **the states** you can have an impact Robert Paun Sidoti company analyst

TABLE III
(CONTINUED)

Firm name	Call date	$PRisk_{i,t}$ (standardized)	Discussion of political risks associated with:	Text surrounding bigram with highest weight $\left(\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}\right)$
National Mentor Holdings, Inc.	12-Feb-2010	42.55	• state and federal budgets; • federal stimulus package; • funding of Medicaid.	governments **both President Obama's 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	9-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 don't 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

TABLE III
(CONTINUED)

Firm name	Call date	$PRisk_{i,t}$ (standardized)	Discussion of political risks associated with:	Text surrounding bigram with highest weight $\left(\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}\right)$
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

TABLE III
(CONTINUED)

Firm name	Call date	$PRisk_{i,t}$ (standardized)	Discussion of political risks associated with:	Text surrounding bigram with highest weight $\left(\frac{f_{b,\mathbb{P}}}{B_{\mathbb{P}}}\right)$
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 table lists 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.

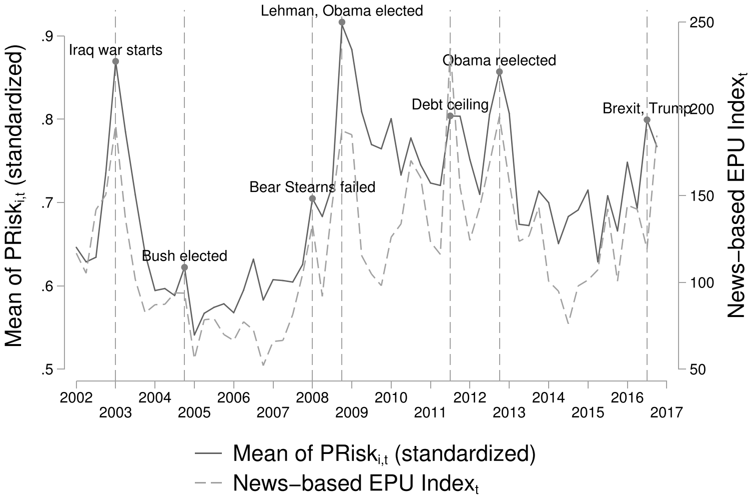

FIGURE I

Variation in $PRisk_{i,t}$ over Time and Correlation with EPU

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 .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 .000.

positives: one in which the word "bet" is not meant to refer to risks associated with the ballot initiative but to betting limits, and another in which "government pressures" are mentioned in proximity to discussion of "currency risks." Nevertheless, these 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 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, $\frac{1}{N}\sum_i PRisk_{it}$, and compares it with the newspaper-based measure of economic policy uncertainty (EPU) constructed by Baker, Bloom, and Davis (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 the series are constructed using very different data sources and methodologies, but nevertheless yield similar results.[14] 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 before and after these elections. We can see that 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 Online 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 two-digit sector and an index of regulatory constraints (Al-Ubaydli and McLaughlin 2017), as well as the share of the sector's revenue accounted for by federal government contracts.

To further probe the properties of our measure, we make use of historical episodes in which a particular political shock is

14. For comparison, Online Appendix Figure II plots the average across firms of our measure of nonpolitical 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.

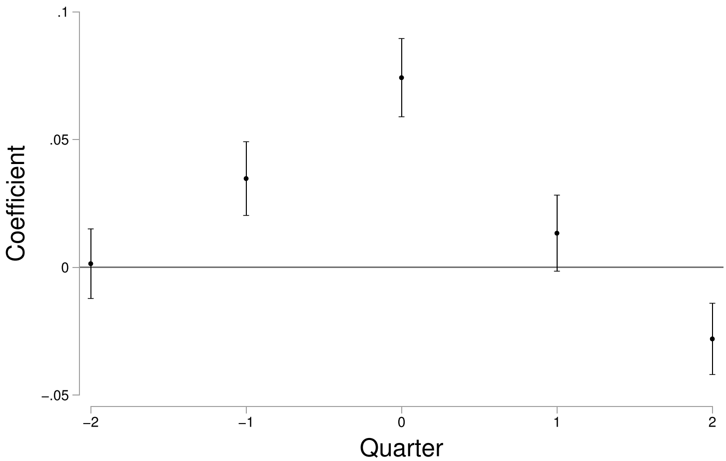

FIGURE II

Variation in $PRisk_{i,t}$ around Federal Elections

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.

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." Online 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.[15] 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).[16]

15. Using business segment data from CapitalIQ, we also verify that these firms do significantly more of their business in the United Kingdom. Regressing the firm's percentage of total sales to the United Kingdom on the number of times the term "Brexit" is used in the third quarter of 2016 yields a coefficient of 0.28 (std. err. = 0.05).

16. 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 $6.15 \times 0.028 = 0.172$ and $6.40 \times 0.140 = 0.896$.

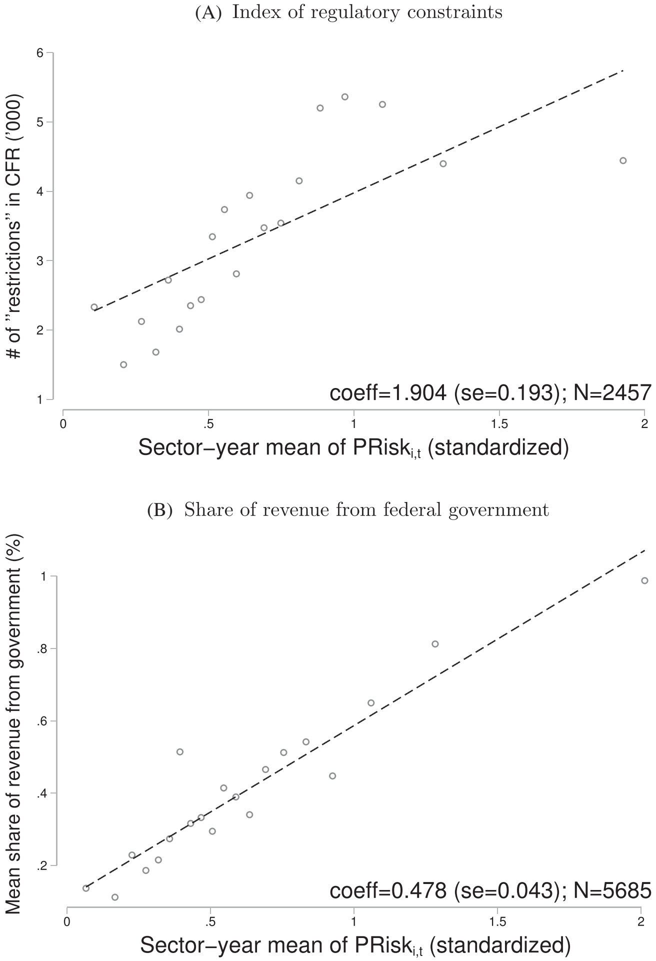

FIGURE III

$PRisk_{i,t}$ and Sector Exposure to Politics

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 (2017). 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.

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.[17]

Table IV, Panel A uses implied stock return volatility, measured using 90-day at-the-money options (again standardized for ease of interpretation). Column (1) shows the 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, std. err. = 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 (std. err. = 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 a factor of 6.74 smaller than in the panel) is associated with a 0.262 standard deviation increase (std. err. = 0.004) in volatility, a number very similar to that documented in previous research (Baker, Bloom, and Davis 2016). Columns (3) and (4) 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, std. err. = 0.005 in column [4]). It also remains statistically significant but falls to 0.016 (std. err. = 0.006) once we go from sector fixed effects to a more demanding specification with firm and CEO

17. To corroborate our choice of standard errors, Online 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 0, with no noticeable tendency for positive or negative estimates. Reassuringly, the rates of false positives and negatives are about 2.5%. Online Appendix Table V shows alternative standard errors clustered by sector and time.

TABLE IV
VALIDATION: IMPLIED AND REALIZED VOLATILITY

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Implied volatility$_{i,t}$ (standardized)						
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)						
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% levels, respectively.

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 that 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 that 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 later.

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.

IV. Managing Political Risk

We 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., Bernanke 1983; Pindyck 1988; Dixit and Pindyck

1994; Bloom, Bond, and Van Reenen 2007).[18] Second, a large literature in political economy predicts that firms have an incentive to "actively" manage political risk by lobbying and donating to politicians (Tullock 1967; Stigler 1971; Peltzman 1976). Third, "active" management of political risks should be concentrated among large but not small firms due to free-rider problems (Olson 1965).

The three panels of Table 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, $\frac{I_{i,t}}{K_{i,t-1}}$, 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 measure the percentage change in projected capital expenditure, $\frac{\Delta \text{capexg}_{i,t}}{\text{capexg}_{i,t-1}}$, as the change (relative to the previous quarter) in the firm's guidance for total capital expenditure for the next fiscal year. Net hiring, $\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}}$, is the change in year-to-year employment over last year's value.[19] All specifications are in the same form as equation (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)–(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 (std. err. = 0.041), a 0.338 percentage point decrease in its planned capital expenditure for the following year (std. err. = 0.120), and a 0.769 percentage point decrease in its employment growth rate (std. err. = 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.[20]

18. 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, 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.

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

20. Because changes in employment are measured at the annual frequency, we show contemporaneous correlations between $PRisk_{it}$ and the outcomes in Panel A.

TABLE V

MANAGING POLITICAL RISK

	(1)	(2)	(3)	(4)
Panel A	$\frac{I_{i,t}}{K_{i,t-1}} * 100$	$\frac{\Delta \text{capexg}_{i,t}}{\text{capexg}_{i,t-1}} * 100$	$\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$	$\frac{\Delta \text{sales}_{i,t}}{\text{sales}_{i,t-1}} * 100$
$PRisk_{i,t}$ (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+$ donations$_{i,t+1}$)	# of recipients$_{i,t+1}$	Hedge$_{i,t+1}$	Log(1+$ lobby$_{i,t+1}$)
$PRisk_{i,t}$ (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+$ donations$_{i,t+1}$)	Log(1+$ lobby$_{i,t+1}$)
$PRisk_{i,t}$ (standardized)	−0.223***	−1.064***	0.025	0.168***
	(0.059)	(0.230)	(0.016)	(0.032)
$PRisk_{i,t} \times \mathbb{1}\{\text{assets}_{i,t} > \text{median assets}\}$	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, $\frac{I_{i,t}}{K_{i,t-1}} * 100$, is calculated recursively using a perpetual-inventory method. Capex guidance, $\frac{\Delta \text{capexg}_{i,t}}{\text{capexg}_{i,t-1}}$, 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, $\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$, 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+$ donations$_{i,t+1}$) (column [1]) is the log of 1 plus the sum of all contributions paid to federal candidates; # of recipients$_{i,t+1}$ (column [2]) is defined as the number of recipients of donations; Hedge$_{i,t+1}$ (column [3]) is a dummy variable equal to 1 if donations to Republicans over donations to Democrats are between the 25th and 75th percentile of the sample; log(1+$ lobby$_{i,t+1}$) (column [4]) is the log of 1 plus total lobby expense. The specifications in Panel C are identical to the ones above but include the interaction between $PRisk_{i,t}$ and a dummy variable that is one if the firm is large (that is, if it has more assets than the median firm). 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% levels, respectively.

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, Bloom, and Davis (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, Bloom, and Davis (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.

Table V, 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 an 8.7% increase in the total amount donated to politicians (std. err. = 0.018) and an increase in the number of donation recipients of 0.462 (std. err. = 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.[21] 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 1 plus the dollar amount

In Panel B, where all outcomes are at the quarterly frequency, we show correlations at the first lag. 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 Online Appendix Table VI, columns (1) and (3).

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

of lobby expenditure on $PRisk_{it}$. The estimate (0.186, std. err. = 0.027) suggests a one standard deviation increase in political risk is associated with an 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. Table V, Panel C 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).[22]

IV.A. *Mean versus Variance of Political Shocks*

Having established that $PRisk_{it}$ correlates with firm actions in a manner highly indicative of political risk, we 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 other controls for the firm's prospects.

To corroborate that $PSentiment_{it}$ indeed contains information about the mean of political shocks, we follow steps similar to those above, showing that transcripts with the most positive (negative) $PSentiment_{it}$ indeed contain significant discussions of positive (negative) news about legislation, regulation, and government spending (see Online Appendix Tables VII and VIII). For example, the transcript with the most negative $PSentiment_{it}$ (Arctic Glacier in May 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 2006) anticipates advantageous

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

changes to the regulation of electricity prices in Vermont. Consistent with these examples, we find that firms tend to experience significantly positive stock returns in quarters when $PSentiment_{it}$ is high. Online 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 precall stock return, accumulated during the seven days prior to the earnings-related conference call, and a conventional measure for the earnings surprise.[23] Again, these variations have little to no effect on our estimates of the association between $PRisk_{it}$ and the

23. 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).

TABLE VI
MEAN VERSUS VARIANCE OF POLITICAL SHOCKS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A	$\frac{I_{i,t}}{K_{i,t-1}} * 100$				$\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$			
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)
PSentiment$_{i,t}$ (standardized)		0.216***				1.181***		
		(0.043)				(0.155)		
Sentiment$_{i,t}$ (standardized)			0.454***				2.252***	
			(0.048)				(0.161)	
Mean stock return 7 days prior$_{i,t}$ (%)				0.025				0.319*
				(0.022)				(0.166)
Earnings announcement 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+$ lobby$_{i,t+1}$)				Log(1+$ donations$_{i,t+1}$)			
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)
PSentiment$_{i,t}$ (standardized)		0.203***				0.117***		
		(0.032)				(0.022)		
Sentiment$_{i,t}$ (standardized)			0.203***				0.115***	
			(0.037)				(0.026)	
Mean stock return 7 days prior$_{i,t}$ (%)				0.028***				0.012***
				(0.007)				(0.004)

TABLE VI
(CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earnings announcement 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 recipients$_{i,t+1}$				Hedge$_{i,t+1}$			
$PRisk_{i,t}$ (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)
$PSentiment_{i,t}$ (standardized)		0.474***				0.008***		
		(0.100)				(0.001)		
Sentiment$_{i,t}$ (standardized)			0.541***				0.007***	
			(0.131)				(0.002)	
Mean stock return 7 days prior$_{i,t}$ (%)				0.032**				0.001**
				(0.013)				(0.000)
Earnings announcement 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 Sentiment$_{i,t}$ are standardized by their standard deviation. Mean stock return 7 days prior$_{i,t}$ (%) is the average stock return for the seven days prior to the earnings call of firm i at date t. Earnings announcement surprise$_{i,t}$ is defined as $\frac{\text{EPS}_{i,t}-\text{EPS}_{i,t-4}}{\text{price}_{i,t}}$, 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. 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% levels, respectively.

firm's actions. We thus find no evidence that managers' incentives to blame political risks for bad performances affect our results.[24]

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.

IV.B. Falsification Exercises

We conduct a series of falsification exercises comparing the information contained in $PRisk_{it}$ with that in our measures of nonpolitical risk ($NPRisk_{it}$) and overall risk ($Risk_{it}$). The results are shown in Table VII. First, all kinds of risk, whether political or nonpolitical, 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 (Panel A, column (2)—all specifications now also control for $PSentiment_{it}$). The coefficient on $NPRisk_{it}$ is negative and statistically significant (−0.255, std. err. = 0.043), whereas the one on $PRisk_{it}$ falls in absolute terms but retains its negative sign and statistical significance (−0.085, std. err. = 0.042).[25] The same pattern, but 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 Panel A, columns (3) and (6), 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, 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

24. Consistent with these results, Online 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 0 when added to these specifications.

25. 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 larger by a factor of about 5 at the quarterly frequency than that of $PRisk_{it}$, so that its coefficients are mechanically inflated.

TABLE VII
FALSIFICATION EXERCISE: POLITICAL RISK, NONPOLITICAL RISK, AND OVERALL RISK

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A		$\frac{I_{i,t}}{K_{i,t-1}} * 100$			$\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$	
$PRisk_{i,\,t}$ (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)
$NPRisk_{i,\,t}$ (standardized)		−0.255***			−0.854***	
		(0.043)			(0.166)	
$Risk_{i,\,t}$ (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+$ lobby$_{i,\,t+1}$)			Log(1+$ donations$_{i,\,t+1}$)	
$PRisk_{i,\,t}$ (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)
$NPRisk_{i,\,t}$ (standardized)		−0.023			−0.004	
		(0.022)			(0.015)	
$Risk_{i,\,t}$ (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

TABLE VII
(CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C	# of recipients$_{i,\,t+1}$			Hedge$_{i,\,t+1}$		
$PRisk_{i,\,t}$ (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)
$NPRisk_{i,\,t}$ (standardized)		−0.042			−0.001	
		(0.052)			(0.001)	
$Risk_{i,\,t}$ (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. $NPRisk_{i,\,t}$ (nonpolitical risk) is calculated in the same way as as $PRisk_{i,\,t}$, but based on nonpolitical 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% levels, respectively.

expenditures on lobbying and donations, as well as the other outcomes proxying for active management of political risk. Neither of the measures of nonpolitical 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 that a given firm faces.

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

IV.C. Choice of Training Libraries and Alternative Implementations of $PRisk_{it}$

Before using our measure to study the nature of political risk faced by U.S. listed firms, we discuss alternative implementations of $PRisk_{it}$. Conditional on the structure given in equation (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 that adding the Santa

Barbara Corpus to the nonpolitical 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 Online Appendix Table XII). Online Appendix Table XIII replicates some of the key findings of the paper with these alternative measures.[26]

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 equation (1). Doing so did not fundamentally alter the sorting of transcripts generated (the correlation with $PRisk_{it}$ is 0.759) 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, Bloom, and Davis (2016, 1599).[27] 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 Online Appendix Tables XIII and XIV.

For use in robustness checks, 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. Online 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 that 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

26. 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 it might induce a backward-looking bias by only identifying political risks of the same nature as those that preoccupied firms in the training sample.

27. 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."

TABLE VIII
VARIANCE DECOMPOSITION OF $PRisk_{it}$

Sector granularity	2-digit SIC (1)	3-digit SIC (2)	4-digit SIC (3)
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 (two-digit SIC) sectors. Columns (2) and (3) use a more granular definition of sectors at the three-digit and four-digit SIC level, respectively. The "firm-level" variation at the annual frequency is 89.47%, 82.12%, and 78.38% at the two-digit, three-digit, and four-digit SIC levels, respectively.

conference calls (Hollander, Pronk, and Roelofsen 2010; Brown and Tucker 2011; Cohen, Malloy, and Nguyen 2018).

V. 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 U.S. 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 a 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 Table VIII, column (1), 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 two-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 refer to this within-sector-and-time variation as "firm-level" or "idiosyncratic" variation in political risk. Although these terms are often used synonymously in the literature, we prefer the former because it avoids confusion with the concept of nonsystematic risk in the finance literature.[28]

Further decomposing this firm-level variation, we find that permanent differences across firms in a given sector (i.e., firm-sector pair fixed effects) account for nearly one quarter (19.87%) of this variation, whereas changes over time in the assignment of political risk across firms within a given sector account for the remainder (i.e., the remaining 71.82% not explained by time or firm fixed effects).[29] These conclusions do not change substantially when we use more granular sector definitions in Table VIII, columns (2) and (3).[30]

At face value, these results are at odds with the conventional view that political events have relatively uniform effects 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 U.S. listed firms, such decisions have differential impacts among subsets of firms and 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

28. However, we show later 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.

29. 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, Clementi, and Lee 2013).

30. 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 $PRisk_{it}$.

variation in the time series (e.g., elections or large-scale reforms).[31]

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 that this variation nevertheless has economic content. In Figure IV, we take this a step further by showing that 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 fixed effects for each firm-sector pair (Panel C).[32] For example, the unconditional correlation between $PRisk_{it}$ and the investment rate is -0.162 (std. err. = 0.043) in Panel A and -0.188 (std. err. = 0.039) in Panel C. (As before, this pattern is largely invariant to using more granular definitions of sectors; see Online Appendix Table XV.) Our results thus suggest that the large amounts of firm-level variation in political risk have real meaning and are not just an artifact of measurement error.

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

31. 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 comove significantly with the EPU measure in the 18 months prior to an election cycle.

32. 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 Online Appendix Table XVI for details).

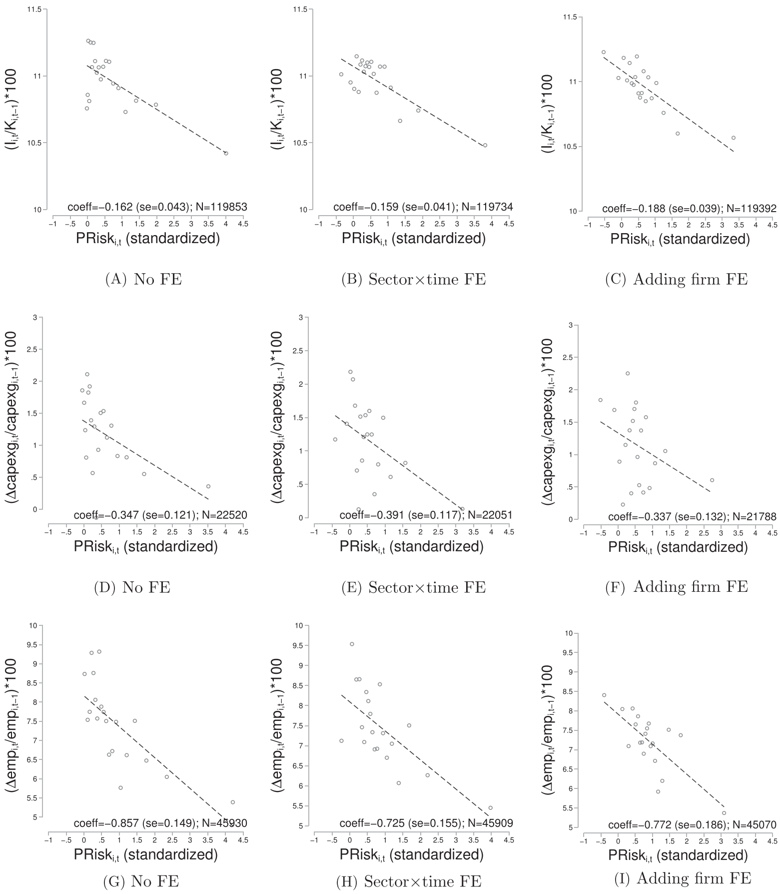

FIGURE IV

Associations between $PRisk_{i,t}$ and Corporate Actions

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, $\frac{I_{i,t}}{K_{i,t-1}} * 100$, (Panels A–C), capex guidance, $\frac{\Delta \text{capexg}_{i,t}}{\text{capexg}_{i,t-1}} * 100$, (Panels D–F), and employment, $\frac{\Delta \text{emp}_{i,t}}{\text{emp}_{i,t-1}} * 100$, (Panels G–I). The left panels show the relations without fixed effects; the middle panels control for sector, time, and sector × time interactions; and the right 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.

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 that 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, Table IX, column (2) 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 that 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 1 plus the dollar amount the firm has outstanding in government contracts as a measure of exposure to aggregate political risk. In each case, including these variables has no effect on the coefficient of interest. Online 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 the 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.

TABLE IX
THE NATURE OF FIRM-LEVEL POLITICAL RISK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Implied volatility$_{i,t}$ (standardized)							
$PRisk_{i,t}$ (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

TABLE IX
(CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B: Realized volatility$_{i,t}$ (standardized)							
$PRisk_{i,t}$ (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's (2016) daily Economic Policy Uncertainty (EPU) Index; rolling betas are constructed by running these regressions using observations only from the eight 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% levels, respectively.

Next we 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.

V.A. 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, Bloom, and Davis 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 also 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 TFP. 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 research studying the microeconomic origins of aggregate fluctuations. Different branches of this literature have argued that idiosyncratic productivity shocks may propagate by affecting 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, Sim, and Zakrajšek 2014; Arellano, Bai, and Kehoe 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 TFP. 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, Saffie, and Shin 2017). Online 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 that the dispersion of firm-level political risk tends to be higher during the 2008–2009 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 (std. err. = 0.0672), implying that a 1 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.[33]

This strong association between aggregate political risk and the dispersion of firm-level political risk suggests that 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 that 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.

V.B. 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 in the information technology sector (Panel B). For each spike

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

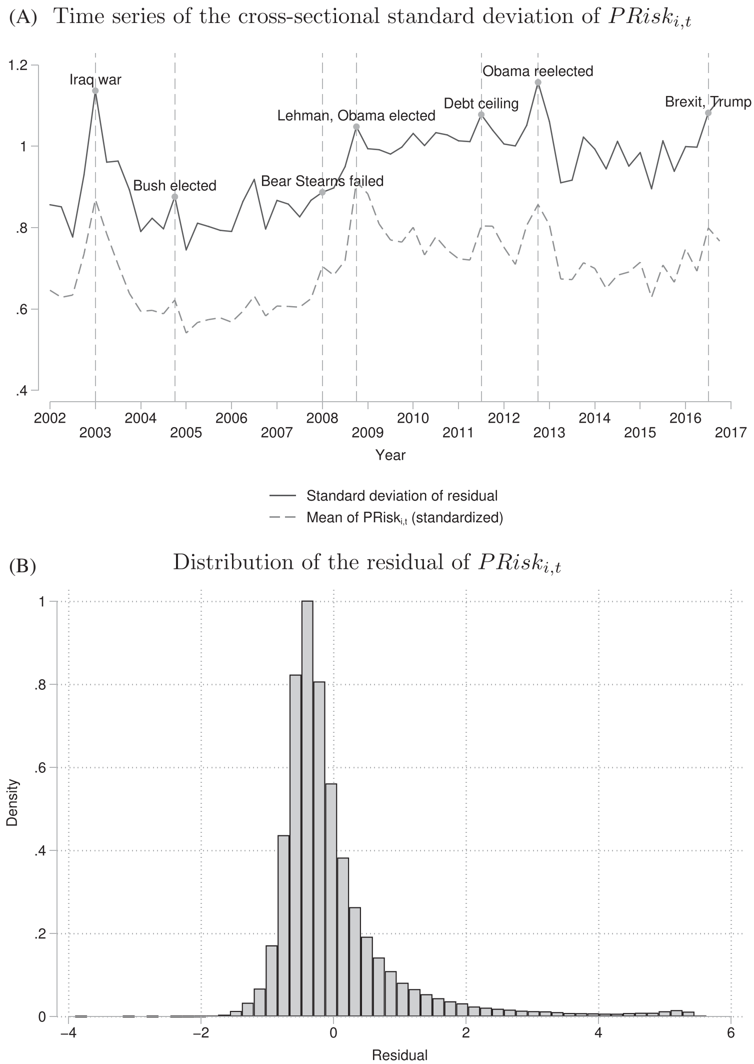

FIGURE V

Dispersion of Firm-Level Political Risk

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 SIC two-digit sector fixed effects. A regression of the former on the latter yields a coefficient of 0.989 (std. err. = 0.0672). $PRisk_{i,\,t}$ 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 0.959; the skewness is 2.797.

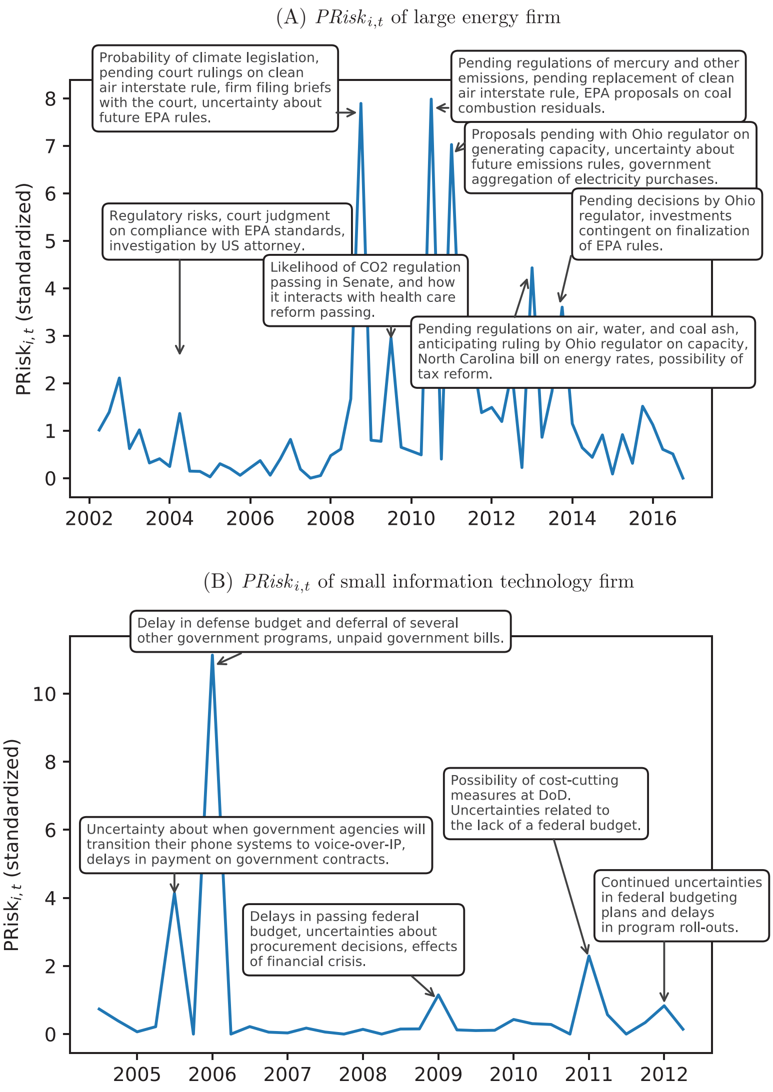

FIGURE VI

Case Studies

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.

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 reformulated, 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.[34] 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 affect 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, we find a noticeable firm-specific element: the firm's executives are rooting for health care reform not because of its effect on the firm's health plan but because it reduces the likelihood of Congress taking up climate legislation.

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.

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

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 very volatile and heterogeneous across firms, such that much of the economically relevant variation of political risk is at the firm level.

VI. Measuring Topic-Specific Political Risk

In the final step of our analysis, we demonstrate that it is possible to generalize our approach in equation (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 nonpolitical library, $\mathbb{N}$, that are used in conjunction with a discussion of political risk:

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

where p is the position of the nearest bigram already counted in our measure of overall political risk in equation (1), that is, a political but not nonpolitical bigram that is also near to a synonym for risk and uncertainty—the nearest bigram for which $\mathbb{1}[b \in \mathbb{P}\backslash\mathbb{N}] \times \mathbb{1}[|b-r| < 10] > 0$. 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, $log\left(\frac{Z}{f_{b,\mathbb{Z}}}\right)$, 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 $log\left(\frac{Z}{Z}\right) = 0$. By contrast, this weight increases the more unique the use of this bigram is when discussing topic T, and is highest ($log\left(\frac{Z}{1}\right)$) for a bigram that is used exclusively in discussion of topic T.

To implement equation (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 and 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."[35]

Mirroring our approach in Section III, 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 effects of three federal budget crises during the Obama presidency on political risk and lobbying.

VI.A. Validation

Online Appendix Table XX shows the top 15 bigrams most indicative of each of our eight political topics: the bigrams with the highest $\frac{f_{b,\mathbb{P}_T}}{B_{\mathbb{P}_T}} log\left(\frac{Z}{f_{b,\mathbb{Z}}}\right)$. 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 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

35. Online Appendix Table XIX gives details on the mapping between the materials provided on the website and these topics.

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: that is, the transcripts of Landry's restaurants, Medcath, Piedmont Natural Gas, and HMS Holdings. However, a closer reading of these transcripts reveals that 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 Online Appendix Table XX (the February 2012 transcript by Yandex, in the "Technology and infrastructure" category).

VI.B. 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 8 political topics (Online Appendix Table I), we generate a dummy variable that equals 1 if firm i lobbies on topic T in quarter t, and 0 otherwise. Our main specification relating this lobbying activity to our topic-based measures of political risk takes the form:

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

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.

Table X, Panel A shows estimates of θ, where column (3) corresponds directly to equation (7). The coefficient estimate (0.794, std. err. = 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 1 plus the dollar expenditure on lobbying as the 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.[36]

VI.C. 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 equation (7) remain.

The first challenge is that an unobserved nonpolitical 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

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

TABLE X
TOPIC-SPECIFIC LOBBYING AND TOPIC-SPECIFIC POLITICAL RISK

	(1)	(2)	(3)	(4)	(5)
Panel A: $\mathbb{1}[\text{lobbying}_{i,t+1}^{T} > 0] * 100$					
$PRisk_{i,t}^{T}$ (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: Log(1+$ $\text{lobby}_{i,t+1}^{T}$)					
$PRisk_{i,t}^{T}$ (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 1 if firm i lobbies on topic T in quarter t+1 (Panel A) and the log of 1 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% levels, respectively.

expenditures before as much as after the discussion of the political topic at hand.

To probe this possibility, Online Appendix Table XXI replicates Table X, column (5)—our most demanding specification relating lagged $PRisk_{it}^{T}$ to lobbying at t+1—while adding contemporaneous and future $PRisk^{T}$ to the regression. The results show that the coefficient on the lag is almost unchanged (0.081, std. err. = 0.030), and it shows a larger effect than both the contemporaneous $PRisk_{i,t+1}^{T}$ (0.064, std. err. = 0.030) and the lead (0.048, std. err. = 0.031), which is statistically indistinguishable from 0. If anything, the lag thus dominates the lead, consistent with a causal interpretation of the results. We interpret this result with caution given the relatively low frequency of the data, the high persistence of lobbying activities,[37] 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 but 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 firm's perspective. In this case, the political risk results from politicians' attempts to minimize adverse effects from the crisis. In other words, a meaningful distinction exists between political risk that fundamentally originates from the political system and political risk that arises due to other forces. Again, disentangling the causal effects of these different types of political risks would require a natural experiment.

Although we have no such natural experiments available, we can nevertheless speak to this issue by making use of three historical case studies that allow us to trace jumps in political risk

37. A pooled regression of $\text{Lobbying}_{i,t+1}(\mathbb{1} * 100)$ on $\text{Lobbying}_{i,t}(\mathbb{1} * 100)$ gives a coefficient of 0.877 (std. err. = 0.056). Lobbying by topic exhibits similarly high persistence (0.882, std. err. = 0.005).

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, not from some other unobserved factor. Moreover, these episodes are associated with unique bigrams that come 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 that 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 (std. err. = 0.937) in the probability that the firm lobbies the government on the same topic in the following quarter. See Online Appendix F for details on these results.

VII. 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 article, 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 nonpolitical 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 firm level, 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 that 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 that 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 (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 TFP 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 find that the dispersion of firm-level political risk comoves 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 (political and nonpolitical), 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, nonpolitical risk, corresponding measures of political and nonpolitical sentiment, as well as additional measures of political risks associated with eight specific political topics. Using these topic-specific measures, we show that firms devoting 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.

Boston University
Tilburg University
Frankfurt School of Finance and Management
London Business School

Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online. Data and code replicating tables and figures in this article can be found in Hassan et al. (2019), in the Harvard Dataverse, doi:10.7910/DVN/OBNRBP.

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "The Network Origins of Aggregate Fluctuations," *Econometrica*, 80 (2012), 1977–2016.

Acemoglu, Daron, Tarek A. Hassan, and Ahmed Tahoun, "The Power of the Street: Evidence from Egypt's Arab Spring," *Review of Financial Studies*, 1 (2018), 1–42.

Acemoglu, Daron, Simon Johnson, Amir Kermani, James Kwak, and Todd Mitton, "The Value of Connections in Turbulent Times: Evidence from the United States," *Journal of Financial Economics*, 121 (2016), 368–391.

Akey, Pat, and Stefan Lewellen, "Policy Uncertainty, Political Capital, and Firm Risk-Taking," London Business School working paper, 2016.

Al-Ubaydli, Omar, and Patrick A. McLaughlin, "RegData: A Numerical Database on Industry-Specific Regulations for All United States Industries and Federal Regulations, 1997–2012," *Regulation & Governance*, 11 (2017), 109–123.

Arayavechkit, Tanida, Felipe Saffie, and Minchul Shin, "Too Big to Pay: Tax Benefits and Corporate Lobbying," Mimeo, University of Maryland, 2017.

Arellano, Cristina, Yan Bai, and Patrick J. Kehoe, "Financial Frictions and Fluctuations in Volatility," NBER Technical report, 2016.

Bachmann, Rüdiger, Steffen Elstner, and Eric R. Sims, "Uncertainty and Economic Activity: Evidence from Business Survey Data," *American Economic Journal: Macroeconomics*, 5 (2013), 217–249.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, 131 (2016), 1593–1636.

Ball, Ray, and Eli Bartov, "How Naive Is the Stock Market's Use of Earnings Information?," *Journal of Accounting and Economics*, 21 (1996), 319–337.

Bekkerman, Ron, and James Allan, "Using Bigrams in Text Categorization," Technical Report IR-408, Center of Intelligent Information Retrieval, UMass Amherst, 2004.

Belo, Frederico, Vito D. Gala, and Jun Li, "Government Spending, Political Cycles, and the Cross Section of Stock Returns," *Journal of Financial Economics*, 107 (2013), 305–324.

Benmelech, Efraim, and Tobias J. Moskowitz, "The Political Economy of Financial Regulation: Evidence from US State Usury Laws in the 19th Century," *Journal of Finance*, 65 (2010), 1029–1073.

Berger, David, Ian Dew-Becker, and Stefano Giglio, "Uncertainty Shocks as Second-Moment News Shocks," NBER Working Paper no. 23796, 2017.

Bernanke, Ben S., "Irreversibility, Uncertainty, and Cyclical Investment," *Quarterly Journal of Economics*, 98 (1983), 85–106.

Besley, Timothy, and Hannes Mueller, "Institutions, Volatility, and Investment," *Journal of the European Economic Association* (2017), jvx030.

Bianco, William T., and David T. Canon, *American Politics Today (Third Essentials Edition)* (New York: McGraw-Hill/Irwin, 2013).

Bloom, Nicholas, "The Impact of Uncertainty Shocks," *Econometrica*, 77 (2009), 623–685.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen Terry, "Really Uncertain Business Cycles," *Econometrica*, 86 (2018), 1031–1065.

Bloom, Nick, Stephen Bond, and John Van Reenen, "Uncertainty and Investment Dynamics," *Review of Economic Studies*, 74 (2007), 391–415.

Born, Benjamin, and Johannes Pfeifer, "Policy Risk and the Business Cycle," *Journal of Monetary Economics*, 68 (2014), 68–85.

Brown, Stephen V., and Jennifer Wu Tucker, "Large-Sample Evidence on Firms' Year-over-Year MD&A Modifications," *Journal of Accounting Research*, 49 (2011), 309–346.

Castro, Rui, Gian Luca Clementi, and Yoonsoo Lee, "Cross–Sectoral Variation in Firm–Level Idiosyncratic Risk," NBER Working Paper no. 17569, 2013.

Cohen, Lauren, Christopher Malloy, and Quoc Nguyen, "Lazy Prices," NBER Working Paper no. 25084, 2018.

Correia, Maria M., “Political Connections and SEC Enforcement,” *Journal of Accounting and Economics*, 57 (2014), 241–262.
Croce, Mariano M., Thien T. Nguyen, and Lukas Schmid, “The Market Price of Fiscal Uncertainty,” *Journal of Monetary Economics*, 59 (2012), 401–416.
De Figueiredo, John M., and Brian S. Silverman, “Academic Earmarks and the Returns to Lobbying,” *Journal of Law and Economics*, 49 (2006), 597–625.
Dixit, Avinash K., and Robert S. Pindyck, *Investment under Uncertainty* (Princeton, NJ: Princeton University Press, 1994).
Dorsey, Jackson, “Waiting on the Courts: Effects of Policy Uncertainty on Pollution and Investment,” Mimeo, University of Arizona, 2017.
Drautzburg, Thorsten, Jesus Fernandez-Villaverde, and Pablo Guerron-Quintana, “Political Distribution Risk and Aggregate Fluctuations,” NBER Working Paper no. 23647, 2017.
Du Bois, John W., Wallace L. Chafe, Charles Meyer, Sandra A. Thompson, and Nii Martey, “Santa Barbara Corpus of Spoken American English,” Philadelphia: Linguistic Data Consortium, 2000.
Faccio, Mara, Ronald W. Masulis, and John McConnell, “Political Connections and Corporate Bailouts,” *Journal of Finance*, 61 (2006), 2597–2635.
Ferguson, Thomas, and Hans-Joachim Voth, “Betting on Hitler—The Value of Political Connections in Nazi Germany,” *Quarterly Journal of Economics*, 123 (2008), 101–137.
Fernandez-Villaverde, Jesus, Luis Garicano, and Tano Santos, “Political Credit Cycles: The Case of the Eurozone,” *Journal of Economic Perspectives*, 27 (2013), 145–166.
Fernández-Villaverde, Jesús, Pablo Guerrón-Quintana, Keith Kuester, and Juan Rubio-Ramírez, “Fiscal Volatility Shocks and Economic Activity,” *American Economic Review*, 105 (2015), 3352–3384.
Fisman, Raymond, “Estimating the Value of Political Connections,” *American Economic Review*, 91 (2001), 1095–1102.
Gabaix, Xavier, “The Granular Origins of Aggregate Fluctuations,” *Econometrica*, 79 (2011), 733–772.
Gennaioli, Nicola, and Andrei Shleifer, *A Crisis of Beliefs: Investor Psychology and Financial Fragility* (Princeton, NJ: Princeton University Press, 2018).
Gentzkow, Matthew, and Jesse M. Shapiro, “What Drives Media Slant? Evidence from US Daily Newspapers,” *Econometrica*, 78 (2010), 35–71.
Giglio, Stefano, Bryan Kelly, and Seth Pruitt, “Systemic Risk and the Macroeconomy: An Empirical Evaluation,” *Journal of Financial Economics*, 119 (2016), 457–471.
Gilchrist, Simon, Jae W. Sim, and Egon Zakrajšek, “Uncertainty, Financial Frictions, and Investment Dynamics,” NBER Technical report, 2014.
Goldman, Eitan, Jörg Rocholl, and Jongil So, “Do Politically Connected Boards Affect Firm Value?,” *Review of Financial Studies*, 22 (2009), 2331–2360.
Gourio, Francois, Michael Siemer, and Adrien Verdelhan, “Uncertainty and International Capital Flows,” Federal Reserve Bank of Chicago, MIT working paper, 2015.
Handley, Kyle, and Nuno Limão, “Trade and Investment under Policy Uncertainty: Theory and Firm Evidence,” *American Economic Journal: Economic Policy*, 7 (2015), 189–222.
Hassan, Tarek A., Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, “Replication Data for: ‘Firm-Level Political Risk: Measurement and Effects’” (2019), Harvard Dataverse, doi: 10.7910/DVN/OBNRBP.
Hassan, Tarek A., and Thomas M. Mertens, “The Social Cost of Near-Rational Investment,” *American Economic Review*, 107 (2017), 1059–1103.
Hollander, Stephan, Maarten Pronk, and Erik Roelofsen, “Does Silence Speak? An Empirical Analysis of disclosure Choices During Conference Calls,” *Journal of Accounting Research*, 48 (2010), 531–563.
Hsieh, Chang-Tai, and Peter Klenow, “Misallocation and Manufacturing TFP in China and India,” *Quarterly Journal of Economics*, 124 (2009), 1403–1448.

Johnson, Simon, and Todd Mitton, "Cronyism and Capital Controls: Evidence from Malaysia," *Journal of Financial Economics*, 67 (2003), 351–382.
Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng, "Measuring Uncertainty," *American Economic Review*, 105 (2015), 1177–1216.
Kang, Karam, "Policy Influence and Private Returns from Lobbying in the Energy Sector," *Review of Economic Studies*, 83 (2016), 269–305.
Kelly, Bryan, Ľuboš Pástor, and Pietro Veronesi, "The Price of Political Uncertainty: Theory and Evidence from the Option Market," *Journal of Finance*, 71 (2016), 2417–2480.
Khwaja, Asim Ijaz, and Atif Mian, "Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market," *Quarterly Journal of Economics*, 120 (2005), 1371–1411.
Koijen, Ralph S. J., Tomas J. Philipson, and Harald Uhlig, "Financial Health Economics," *Econometrica*, 84 (2016), 195–242.
Leuz, Christian, and Felix Oberholzer-Gee, "Political Relationships, Global Financing, and Corporate Transparency: Evidence from Indonesia," *Journal of Financial Economics*, 81 (2006), 411–439.
Li, Feng, Russell Lundholm, and Michael Minnis, "A Measure of Competition Based on 10-K Filings," *Journal of Accounting Research*, 51 (2013), 399–436.
Libby, Robert, Patricia A. Libby, and Daniel G. Short, *Financial Accounting* (New York: McGraw-Hill/Irwin, 2011).
Loughran, Tim, and Bill McDonald, "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks," *Journal of Finance*, 66 (2011), 35–65.
———, "Textual Analysis in Accounting and Finance: A Survey," *Journal of Accounting Research*, 54 (2016), 1187–1230.
Manning, Christopher D., Prabhakar Raghavan, and Hinrich Schütze, *Introduction to Information Retrieval* (Cambridge: Cambridge University Press, 2008).
Matsumoto, Dawn, Maarten Pronk, and Erik Roelofsen, "What Makes Conference Calls Useful? The Information Content of Managers' Presentations and Analysts' Discussion Sessions," *Accounting Review*, 86 (2011), 1383–1414.
Milyo, Jeffrey, David Primo, and Timothy Groseclose, "Corporate PAC Campaign Contributions in Perspective," *Business and Politics*, 2 (2000), 75–88.
Mishra, Apra, and Santosh Vishwakarma, "Analysis of TF-IDF Model and Its Variant for Document Retrieval," in *2015 International Conference on Computational Intelligence and Communication Networks (CICN)*, (2015), 772–776.
Mueller, Philippe, Alireza Tahbaz-Salehi, and Andrea Vedolin, "Exchange Rates and Monetary Policy Uncertainty," *Journal of Finance*, 72 (2017), 1213–1252.
Olson, Mancur, *The Logic of Collective Action* (Cambridge, MA: Harvard University Press, 1965).
Pastor, Lubos, and Pietro Veronesi, "Uncertainty about Government Policy and Stock Prices," *Journal of Finance*, 67 (2012), 1219–1264.
———, "Political Uncertainty and Risk Premia," *Journal of Financial Economics*, 110 (2013), 520–545.
Peltzman, Sam, "Toward a More General Theory of Regulation," *Journal of Law and Economics*, 19 (1976), 211–240.
Pindyck, Robert S., "Irreversible Investment, Capacity Choice, and the Value of the firm," *American Economic Review*, 78 (1988), 969.
Ramos, Juan, "Using Tf-Idf to Determine Word Relevance in Document Queries," in *Proceedings of the First Instructional Conference on Machine Learning* (2003).
Roberts, Brian E., "A Dead Senator Tells No Lies: Seniority and the Distribution of Federal Benefits," *American Journal of Political Science*, 34 (1990), 31–58.
Salton, Gerard, and Christopher Buckley, "Term-Weighting Approaches in Automatic Text Retrieval," *Information Processing and Management*, 24 (1988), 513–523.
Salton, Gerard, and Michael McGill, *Introduction to Modern Information Retrieval* (New York: McGraw-Hill, 1983).

Snowberg, Erik, Justin Wolfers, and Eric Zitzewitz, “Partisan Impacts on the Economy: Evidence from Prediction Markets and Close Elections,” *Quarterly Journal of Economics*, 122 (2007), 807–829.
Song, Min, and Yi-fang B. Wu, *Handbook of Research on Text and Web Mining Technologies* (Hershey, PA: IGI Global, 2008).
Sparck Jones, Karen, “A Statistical Interpretation of Term Specificity and its Application in Retrieval,” *Journal of Documentation*, 28 (1972), 11–21.
Stein, Luke C. D., and Elizabeth C. Stone, “The Effect of Uncertainty on Investment, Hiring, and R&D: Causal Evidence from Equity Options,” Working paper, 2013, (SSRN 1649108).
Stigler, George J., “The Theory of Economic Regulation,” *Bell Journal of Economics and Management Science*, 2 (1971), 3–21.
Tahoun, Ahmed, “The Role of Stock Ownership by US Members of Congress on the Market for Political Favors,” *Journal of Financial Economics*, 111 (2014), 86–110.
Tahoun, Ahmed, and Laurence van Lent, “The Personal Wealth Interests of Politicians and Government Intervention in the Economy,” *Review of Finance*, 23 (2019), 37–74.
Tan, Chade-Meng, Yuan-Fang Wang, and Chan-Do Lee, “The Use of Bigrams To Enhance Text Categorization,” *Information Processing & Management*, 38 (2002), 529–546.
Tullock, Gordon, “The Welfare Costs of Tariffs, Monopolies, and Theft,” *Western Economic Journal*, 5 (1967), 224–232.

CALL FOR NOMINATIONS

$300,000 Nemmers Prize in Economics

Northwestern University invites nominations for the Erwin Plein Nemmers Prize in Economics, to be awarded during the 2026–27 academic year. The prize pays the recipient $300,000. Recipients of the Nemmers Prize present lectures, participate in department seminars, and engage with Northwestern faculty and students in other scholarly activities.

Details about the prize and the nomination process can be found at **nemmers.northwestern.edu**. Candidacy for the Nemmers Prize is open to those with careers of outstanding achievement in their disciplines as demonstrated by major contributions to new knowledge or the development of significant new modes of analysis.Individuals of all nationalities and institutional affiliations are eligible except current or recent members of the Northwestern University faculty and past recipients of the Nemmers or Nobel Prize. **Nominations will be accepted until January 14, 2026.**

The Nemmers prizes are made possible by a generous gift to Northwestern University by the late Erwin Esser Nemmers and the late Frederic Esser Nemmers.

Northwestern

Nemmers Prizes • Office of the Provost • Northwestern University • Evanston, Illinois 60208
nemmers.northwestern.edu