The Quarterly Journal of Economics Advance Access published July 11, 2016

Corresponding Author: Steven Davis, Booth School of Business, University of Chicago, 5807 South Woodlawn Avenue, Chicago IL, 60637, 773 702 7312, Steven.Davis@chicagobooth.edu

MEASURING ECONOMIC POLICY UNCERTAINTY*

SCOTT R BAKER

NICHOLAS BLOOM

STEVEN J DAVIS

We develop a new index of economic policy uncertainty (EPU) based on newspaper coverage frequency. Several types of evidence – including human readings of 12,000 newspaper articles – indicate that our index proxies for movements in policy-related economic uncertainty. Our US index spikes near tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the failure of Lehman Brothers, the 2011 debt-ceiling dispute and other major battles over fiscal policy. Using firm-level data, we find that policy uncertainty is associated with greater stock price volatility and reduced investment and employment in policy-sensitive sectors like defense, healthcare, finance and infrastructure construction. At the macro level, innovations in policy uncertainty foreshadow declines in investment, output, and employment in the United States and, in a panel VAR setting, for 12 major economies. Extending our US index back to 1900, EPU rose dramatically in the 1930s (from late 1931) and has drifted upwards since the 1960s.
JEL Codes: D80, E22, E66, G18 and L50

* We thank Adam Jorring, Kyle Kost, Abdulla Al-Kuwari, Sophie Biffar, Jörn Boehnke, Vladimir Dashkeyev, Olga Deriy, Eddie Dinh, Yuto Ezure, Robin Gong, Sonam Jindal, Ruben Kim, Sylvia Klosin, Jessica Koh, Peter Lajewski, David Nebiyu, Rebecca Sachs, Ippei Shibata, Corinne Stephenson, Naoko Takeda, Melissa Tan, Sophie Wang and Peter Xu for research assistance and the National Science Foundation, MacArthur Foundation, Sloan Foundation Becker Friedman Institute, Initiative on Global Markets, and Stigler Center at the University of Chicago for financial support. We thank Ruedi Bachmann, Sanjai Bhagat, Vincent Bignon, Yongsung Chang, Vladimir Dashkeyev, Jesus Fernandez-Villaverde, Laurent Ferrara, Luis Garicano, Matt Gentzkow, Yuriy Gorodnichenko, Kevin Hassett, Takeo Hoshi, Greg Ip, Anil Kashyap, Patrick Kehoe, John Makin, Johannes Pfeifer, Meijun Qian, Itay Saporta, John Shoven, Sam Schulhofer-Wohl, Jesse Shapiro, Erik Sims, Stephen Terry, Cynthia Wu and many seminar and conference audiences for comments. We also thank the referees and editors, Robert Barro and Larry Katz, for comments and suggestions.

I. INTRODUCTION

Concerns about policy uncertainty have intensified in the wake of the Global Financial Crisis, serial crises in the Eurozone, and partisan policy disputes in the United States. For example, the Federal Open Market Committee (2009) and the IMF (2012, 2013) suggest that uncertainty about U.S. and European fiscal, regulatory, and monetary policies contributed to a steep economic decline in 2008-09 and slow recoveries afterwards.[1]

To investigate the role of policy uncertainty, we first develop an index of economic policy uncertainty (EPU) for the United States and examine its evolution since 1985.[2] Our index reflects the frequency of articles in 10 leading US newspapers that contain the following triple of words: "economic" or "economy"; "uncertain" or "uncertainty"; and one or more of "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". As seen in Figure I, the index spikes near tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the 2011 debt-ceiling dispute and other major battles over fiscal policy. We extend our newspaper-based approach to measuring policy uncertainty along three dimensions: back in time, across countries, and to specific policy categories.

To push back to 1900, we rely on archives for six major US newspapers published throughout the last century. As shown in Figure II, this long-span EPU index highlights pre-World War II political developments and shocks like the Gold Standard Act of 1900, the outbreak of World War I, the Versailles conference in 1919, and a sustained surge in policy uncertainty from late 1931 when President Hoover, and then President Roosevelt, introduced a rash of major new policies. The index also shows an upward drift since the 1960s, perhaps due to rising political polarization or the growing economic role for government (Baker et al., 2014).

Using similar methods, we construct EPU indices for eleven other countries, including all G10 economies. These indices are particularly helpful in countries with fewer alternative uncertainty measures. We also develop category-specific policy uncertainty indices for the US by specifying more restrictive criteria for those articles that contain our triple of terms about the economy, policy, and uncertainty. As examples, Figure III plots indices of healthcare policy uncertainty and national security policy uncertainty based on the presence of additional terms

[1] "[W]idespread reports from business contacts noted that uncertainties about health-care, tax, and environmental policies were adding to businesses' reluctance to commit to higher capital spending." (FOMC minutes, 15-16 December 2009) See, also, IMF (2012, pages xv-xvi and 49-53, and 2013, pages 70-76).

[2] Our data are available at monthly and daily frequencies on www.policyuncertainty.com and are carried by Bloomberg, Haver, FRED and Reuters.

like "healthcare", "hospital" or "health insurance" and "war", "terrorism" or "department of defense", respectively. Category-specific shocks and policy initiatives are clearly visible.

Our approach to measuring policy uncertainty raises potential concerns related to newspaper reliability, accuracy, bias, and consistency. To address these concerns, we evaluate our EPU index in several ways. First, we show a strong relationship between our measure of economic policy uncertainty and other measures of *economic uncertainty,* e.g., implied stock-market volatility. Second, we also show a strong relationship between our index and other measures of *policy uncertainty*, e.g., the frequency with which the Federal Reserve System's Beige Books mention policy uncertainty. Third, we find very similar movements in EPU indices based on right-leaning and left-leaning newspapers, suggesting that political slant does not seriously distort our overall EPU index.

Fourth, we conducted an extensive audit study of 12,000 randomly selected articles drawn from major US newspapers. Working under our close supervision, teams of University of Chicago students underwent a training process and then carefully read overlapping sets of articles, guided by a 65-page reference manual and weekly team meetings. The auditors assessed whether a given article discusses economic policy uncertainty based on our criteria. We use the audit results to select our policy term set, evaluate the performance of our computer-automated methods, and construct additional data. There is a high correlation between our human- and computer-generated indices (0.86 in quarterly data from 1985 to 2012 and 0.93 in annual data from 1900 to 2010). The discrepancy between the human and computer-generated indices is uncorrelated with GDP growth rates and with the level of economic policy uncertainty.

Finally, our indices have a market-use validation: Commercial data providers that include Bloomberg, FRED, Haver and Reuters carry our indices to meet demands from banks, hedge funds, corporates and policy makers. This pattern of market adoption suggests that our indices contain useful information for a range of decision makers.

In Section IV we provide evidence of how firm-level and aggregate outcomes evolve in the wake of policy uncertainty movements. Causal inference is challenging, because policy responds to economic conditions, and is likely to be forward looking. To make progress we follow a micro and a macro estimation approach. First, the micro approach exploits firm-level differences in exposure to certain aspects of policy, mainly government purchases of goods and services. We use micro data from the Federal Registry of Contracts and data on government healthcare spending to calculate the share of firm and industry revenues derived from sales to the government. Next, in firm-level regressions that include time and firm fixed effects and other controls, we show that firms with greater exposure to government purchases experience greater stock price volatility when policy uncertainty is high and reduced investment rates and employment growth when policy uncertainty rises. Adding the VIX as an explanatory variable (interacted with firm-level exposure to government purchases), we still find greater stock-price volatility, and falls in investment and employment with heightened policy uncertainty, which points to a policy uncertainty channel at work rather than a broader uncertainty effect. We also find that firms in the defense, healthcare and financial sectors are especially responsive to their own category-specific EPU measures, confirming their information value.

These firm-level results are suggestive of a causal impact of policy uncertainty on investment and employment in sectors that rely heavily on government spending and in sectors like healthcare and finance with strong exposure to major shifts in regulatory policy. However, the firm-level results offer limited guidance about the magnitude of aggregate effects, in part because they capture only a limited set of potential policy uncertainty channels.

Our second approach fits vector autoregressive (VAR) models to US data and to an international panel VAR that exploits our EPU indices for 12 countries. The US VAR results indicate that a policy uncertainty innovation equivalent to the actual EPU increase from 2005-06 to 2011-12 foreshadows declines of about 6% in gross investment, 1.2% in industrial production and 0.35% in employment. The 12-country panel VAR yields similar results.[3] While our results are not necessarily causal, one plausible interpretation of our micro and macro evidence is that policy uncertainty retards investment, hiring and growth in policy sensitive sectors like defense, finance, healthcare and construction, and these sectors are important enough for policy uncertainty to matter at the aggregate level.

This paper relates to at least three literatures. The first is research on the impact of uncertainty on growth and investment. Theoretical work on this topic dates at least to Bernanke (1983), who points out that high uncertainty gives firms an incentive to delay investment and

[3] Stock and Watson (2012) use our EPU index to investigate the factors behind the 2007-2009 recession and slow recovery and come to a similar conclusion – namely, that policy uncertainty is a strong candidate to partly explain the poor economic performance, but causal identification is hard.

hiring when investment projects are costly to undo or workers are costly to hire and fire.[4] Of course, once uncertainty recedes, firms increase hiring and investment to meet pent-up demand. Other reasons for a depressive effect of uncertainty include precautionary spending cutbacks by households, upward pressure on the cost of finance (e.g., Gilchrist et al., 2014, and Pastor and Veronesi, 2013), managerial risk-aversion (e.g., Panousi and Papanikolaou, 2012), and interactions between nominal rigidities and search frictions (Basu and Bundick, 2015 and Leduc and Liu, 2015).

Second, there is a literature focused explicitly on policy uncertainty. Friedman (1968), Rodrik (1991), Higgs (1997) and Hassett and Metcalf (1999), among others, consider the detrimental economic effects of monetary, fiscal, and regulatory policy uncertainty. More recently, Born and Pfeifer (2014) and Fernandez-Villaverde at al. (2015) study policy uncertainty in DSGE models, finding moderately negative effects, while Pastor and Veronesi (2012, 2013) model the theoretical links among fluctuations, policy uncertainty, and stock market volatility.[5]

Finally, there is a rapidly growing literature on text search methods – using newspaper archives, in particular – to measure a variety of outcomes. Examples include Gentzkow and Shapiro (2010), Hoberg and Phillips (2010), Boudoukh et al. (2013), and Alexopoulos and Cohen (2015). Our work suggests that newspaper text search can yield useful proxies for economic and policy conditions stretching back several decades, which could be especially valuable in earlier eras and in countries with fewer data sources.

Section II describes the data we use to construct our policy uncertainty indices. Section III evaluates our EPU measures in several ways and develops additional evidence about movements in policy-related uncertainty over time. Section IV investigates how firm-level outcomes covary with policy uncertainty and the dynamic responses of aggregate outcomes to

[4] Dixit and Pindyck (1994) offer a review of the early theoretical literature, including papers by Oi (1961), Hartman (1972) and Abel (1983) that highlight potentially positive effects of uncertainty. Recent empirical papers include Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta and Terry (2014), Bachman et al. (2013) and Scotti (2014), with a review in Bloom (2014).

[5] In other related work, Julio and Yook (2012) find that investment falls around national elections, Durnev (2010) finds that corporate investment becomes less responsive to stock prices in election years, Brogaard and Detzel (2015) find that policy uncertainty reduces asset returns, Handley and Limao (2015) find that trade-policy uncertainty delays firm entry, Gulen and Ion (2016) find negative responses of corporate investment to our EPU index, Koijen et al. (2016) develop evidence that government-induced uncertainty about profitability generates a large equity risk premium for firms in the healthcare sector and reduces their medical R&D, and Giavazzi and McMahon (2012) find that policy uncertainty led German households to increase savings in the run-up to the close and consequential general elections in 1998.

policy uncertainty innovations. Section V concludes and offers some thoughts about directions for future research.

II. MEASURING ECONOMIC POLICY UNCERTAINTY

We build indices of policy-related economic uncertainty based on newspaper coverage frequency.[6] We aim to capture uncertainty about *who* will make economic policy decisions, *what* economic policy actions will be undertaken and *when*, and the economic *effects* of policy actions (or inaction) – including uncertainties related to the economic ramifications of “non-economic” policy matters, e.g., military actions. Our measures capture both near-term concerns (e.g., when will the Fed adjust its policy rate) and longer-term concerns (e.g., how to fund entitlement programs), as reflected in newspaper articles. We first describe the construction of our monthly and daily EPU indices for the US from 1985 onwards and then turn to indices for specific policy categories, indices for other countries, and historical indices for the US and UK.

II.A. US economic policy uncertainty indices from 1985

Our modern monthly EPU index for the US relies on 10 leading newspapers: USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and Wall Street Journal. We search the digital archives of each paper from January 1985 to obtain a monthly count of articles that contain the following triple of words: ‘uncertainty’ or ‘uncertain’; ‘economic’ or ‘economy’; and one of the following policy terms: ‘congress’, ‘deficit’, ‘Federal Reserve’, ‘legislation’, ‘regulation’ or ‘white house’ (including variants like ‘uncertainties’, ‘regulatory’ or ‘the Fed’). In other words, to meet our criteria, an article must contain terms in all three categories pertaining to uncertainty, the economy, and policy. We use our audit study to select the policy terms, as explained in Section III.A.

An obvious difficulty with these raw counts is that the overall volume of articles varies across newspapers and time. Thus, we scale the raw counts by the total number of articles in the same newspaper and month. We standardize each monthly newspaper-level series to unit

[6] Earlier drafts of this paper include index components based on (a) the present value of future scheduled tax code expirations and (b) disagreement among professional forecasters over future government purchases and consumer prices. However, to extend our EPU measures over time and across countries, we focus here on the newspaper approach, while continuing to report the other components at www.policyuncertainty.com.

standard deviation from 1985 to 2009 and then average across the ten papers by month. Finally, we normalize the 10-paper series to a mean of 100 from 1985 to 2009. To be precise, let X_{it} denote the scaled EPU frequency counts for newspaper *i*=1, 2, … 10 in month *t,* and let T_1 and T_2 denote the time intervals used in the standardization and normalization calculations. We proceed in the following steps: (1) Compute the times-series variance, σ_i^2, in the interval T_1 for each paper *i.* (2) Standardize X_{it} by dividing through by the standard deviation σ_i for all *t.* This operation yields, for each paper, a series Y_{it} with unit standard deviation in the interval T_1. (3) Compute the mean over newspapers of Y_{it} in each month to obtain the series Z_t. (4) Compute *M,* the mean value of Z_t in the interval T_2. (5) Multiply Z_t by (100/M) for all *t* to obtain the normalized EPU time-series index. We use the same approach for other countries and indices.

Figure I plots the resulting index, which shows clear spikes around the Gulf Wars, close presidential elections, the 9/11 terrorist attack, the 2009 stimulus debate, the Lehman Brothers bankruptcy and TARP legislation in late 2008, the summer 2011 debt-ceiling dispute and the battle over the "Fiscal Cliff" in late 2012, among other events and developments. Some notable political events do not generate high EPU according to our index. For instance, our EPU index shows no large spike in connection with the partial federal government shutdowns from November 1995 to January 1996, although those shutdowns received much press coverage.[7]

In addition to our monthly index, we also produce a daily EPU index using the Newsbank news aggregator, which covers around 1,500 US newspapers. Newsbank's extensive coverage yields enough articles to generate a meaningful daily count. Taking monthly averages of our daily index, it correlates at 0.85 with our 10-paper monthly index, indicating a high degree of similarity. Because papers enter and exit the Newsbank archive, and its count of newspapers expands greatly over time, compositional shifts potentially distort the longer-term behavior of the daily EPU index. Hence, we focus below on our 10-paper monthly EPU index, but the daily index provides a useful high-frequency alternative.[8]

II.B. EPU indices for policy categories

[7] We find more than 8,000 articles about these shutdowns in Newsbank archives, but less than 25% also mention the economy, less than 2% mention uncertainty, and only 1% mentions both. Thus, politically tumultuous episodes do not necessarily raise economic policy uncertainty, at least by our measure.

[8] We update the daily EPU index at approximately 9am EST each day and post it at www.policyuncertainty.com.

To create indices for policy categories, we apply additional criteria to those articles that contain our triple of terms about the economy, policy and uncertainty. The additional criteria involve the presence of one or more category-relevant terms: "the Fed", "central bank", "interest rate", "inflation" and so on for the monetary policy category, for example. Online Appendix B reports the full set of terms that define our eleven policy categories and sub-categories. We use Newsbank for the category indices, because its high text density facilitates measurement by time period and policy category. As seen in Figure III, the national security EPU index spiked sharply in connection with the 9/11 attacks, Gulf War I and the onset of Gulf War II. The healthcare EPU index rose sharply during the Clinton healthcare reform initiative in 1993-94 and has fluctuated at high levels from 2009 to 2014.

Table I reports all eleven category-specific EPU indices.[9] It also reports an overall Economic Uncertainty ("EU") index that drops the policy requirement in the EPU index. The first two rows report average EU and EPU values for the indicated periods, expressed relative to the average EPU value from 1985 to 2014. For example, the EU value of 218.2 says the (scaled) frequency of EU articles from 1985:1 to 1990:6 is somewhat more than twice the average frequency of EPU articles from 1985 to 2014. The next eleven rows report relative frequency values for specific policy categories and time periods. For example, the 54.8 value for "National Security" says the frequency of EPU articles during 2001:9 to 2002:12 that mention national security matters is 54.8 percent of the 1985-2014 average EPU frequency and 43 percent (54.8/(0.39*326.9)) of the EPU frequency from 2001:9 to 2002:12.

Fiscal matters, especially tax policy, stand out in Table I as the largest source of policy uncertainty, especially in recent years. The fiscal policy EPU index rose from values near 33 in the pre-crisis years to 61.5 in 2008:9 to 2009:12 and 78.3 from 2010 to 2013. Healthcare policy is the second largest source of elevated EPU in recent years. Policy uncertainty related to financial regulations and entitlement programs also rose sharply after 2008, but from initially lower levels. Concerns related to sovereign debt and currency crises are up by an order of magnitude during 2010 to 2013, but from such a low base as to have little impact on the overall EPU index. EPU concerns related to monetary policy are important throughout the 1985-2014 period, but perhaps surprisingly, they are not elevated in recent years by our measure. We

[9] In contrast to Figure III, which normalizes each category-specific EPU series to 100, Table I expresses each category-specific EPU series as a percentage of the overall EPU frequency from 1985 to 2014.

interpret this result as a reflection of low and stable inflation rates in recent years, which apparently drive newspaper coverage more than disputes among professional economists about unconventional monetary policies.[10]

Several other researchers develop measures related to uncertainty about government behavior. Marina Azzimonti (2015) constructs a newspaper index of partisan conflict at the federal level that shows similarities to our EPU index but also notable departures – e.g., war and national security threats produce declines in partisan conflict but increases in policy uncertainty. Shoag and Veuger (2015) develop policy uncertainty indices for US states based on newspapers and other local indicators, finding a strong negative link to state-level economic performance. Fernandez-Villaverde et al. (2015) estimate stochastic volatility processes for US capital taxes, labor taxes and government expenditures in a DSGE model, finding correlations with our EPU index of 0.44, 0.31, and 0.67, respectively. Jurado, Ludvigson, and Ng (2015) derive uncertainty measures from common variation in the unforecastable components of macroeconomic indicators, with their main measure correlating at 0.42 with our EPU index.

II.C. EPU indices for other countries

We also construct EPU indices for eleven other major economies.[11] As with our US index, we first obtain a monthly count of articles that contain a triple of terms about the economy (E), policy (P) and uncertainty (U). We then scale the raw counts, standardize each newspaper's variation, average across papers in a country by month, and normalize.[12] To help develop suitable E, P and U term sets, we consulted persons with native-level fluency and economics expertise in the relevant language and country. Our P term set differs across countries for reasons both obvious (e.g., using "BOJ" for Japan) and idiosyncratic (e.g., inclusion of "customs duties" for India). Online Appendix A lists the term sets and newspapers for each country-level EPU index. We perform all searches in the native language of the newspaper, drawing on archives for

[10] Other evidence also points to subdued levels of inflation uncertainty in recent years. See Nalewaik (2015) for a presentation and discussion of evidence based on time-series models, surveys and financial markets data.
[11] We have also assisted other researchers in developing EPU indices for Holland, and are currently collaborating to develop additional EPU indices for Argentina, Australia, Brazil and Japan. We are open to proposals to develop indices for other countries.
[12] For certain papers outside the US, search platform limitations preclude us from scaling by the count of all articles. In these cases, we instead scale by the count of articles containing the common and neutral term "today".

seven newspapers in India, six each in Canada and South Korea, two each in France, Germany, Italy, Japan, Spain and the United Kingdom, and one each in China and Russia.[13]

Figure IV displays the EPU index for Russia, and Online Appendix Figures A1-A10 display the other country-level indices.[14] The Russian index responds to Russian military conflicts, major political developments in Ukraine, the Russian Financial Crisis in 1998, the Lehman Brothers failure in 2008, the 2013 "taper tantrum" triggered by a perceived shift in US monetary policy, and other developments. While the Russian index is noisy, reflecting our reliance on a single paper, it shows that our approach yields useful information even for countries with strong restrictions on press freedoms. Looking at EPU indices across twelve countries, we see that a wide variety of global and domestic factors drive movements in our newspaper-based measures of policy uncertainty.

II.D. Long-span EPU indices for the US and UK

We also construct long-span monthly EPU indices back to 1900 for the United States (drawing on digital archives for the Wall Street Journal, New York Times, Los Angeles Times, Boston Globe, Chicago Tribune and Washington Post) and the United Kingdom (Times of London and the Guardian). Based on informal audits and our review of word usage patterns in newspapers and other text sources, we expanded the E term set for the historical indices to include "business", "industry", "commerce" and "commercial". The expanded and narrower E term sets yield very similar results in recent decades, but the expanded set seems to perform better in the early decades of the 20th century. Based on results of the audit analysis described below, we also expanded the P term set for the historical indices to include "tariff" and "war".

Figure II and appendix Figure A1 display the historical EPU indices for the US and UK. Indices for these two countries exhibit both similarities and notable differences. For example, the elevation of EPU levels in the 1930s is dramatic in the US but modest in the UK, which experienced a less severe output fall during the Great Depression. World Wars I and II are more prominent in the UK EPU series. Gulf Wars I and II are associated with sharp EPU spikes in both countries. The mid 1970s stands out as a period of unusually high EPU in the UK (which suffered severe economic turmoil over this period, including the IMF bail-out and resignation of

[13] Censorship and state control of the media present special challenges for Russia and China. For China, we use the South China Morning Post, the leading English-language newspaper in Hong Kong. For Russia, we rely on Kommersant, which focuses on financial matters and is reportedly fairly free of government pressures.
[14] We provide regular monthly updates of the country-level EPU indices at www.policyuncertainty.com.

Prime Minister Harold Wilson) but not in the US. The post-1960s upward drift of EPU evident for the US is absent for the UK. This long-span US-UK comparison reinforces our earlier inference that a broad mix of domestic and international developments influences the extent of policy uncertainty in any given country.

III. EVALUATING OUR POLICY UNCERTAINTY MEASURES

As remarked in the Introduction, using newspaper-based measures of economic policy uncertainty raises several issues about accuracy and potential bias. This section explains how we sought to address those issues. We start with a discussion of our audit study, which relies on human readings of newspaper articles. We use the audit study to select our P term set, compare the time-series behavior of human and computer-generated EPU indices, and collect other information about the nature of policy uncertainty. Next, we consider the role of political slant in our EPU index. Lastly, we compare our newspaper-based index to other measures of uncertainty: stock market volatility, the frequency of uncertainty and policy uncertainty discussions in the Beige Books, the share of the "Risk Factors" section in firms' 10-K filings devoted to government policies and regulations, and the frequency of large daily stock market moves triggered by news about government policy.

III.A. Audit Study Based on Human Readings

We spent six months developing an audit process designed to evaluate and refine our US EPU indices and another 18 months running a large-scale human audit study. During the latter phase, student teams working under our close supervision read and coded articles drawn from eight newspapers from 1900 to 2012.[15] We now describe the audit process and results.

Audit process: We began by reading a few hundred newspaper articles, typically in batches of fifty, and comparing notes to develop classification criteria, an audit template in the form of an Excel file, and the first draft of a guidebook for auditors. Early on, we concluded that the largest payoff to an audit study involved selecting and evaluating the "policy" or P term set. Accordingly, the formal audit study described below samples from the universe of articles that

[15] To construct our EPU index, it suffices to recover counts of articles that contain certain terms. In contrast, we need full-text articles (machine-readable files or images) to carry out the audit study. We could not access full-text articles for the Boston Globe or USA Today, but we did so for the other eight newspapers.

meet our "economy" and "uncertainty" criteria, which concentrates our (expensive) human resources on samples that are highly germane for our purposes.[16]

Next, we conducted a pilot audit. Working with a team of student research assistants, we read and coded 2,000 randomly selected newspaper articles. To identify coding difficulties and weaknesses in our training materials, we held weekly review sessions with the auditors and assigned about 20% of articles to multiple auditors. We used the pilot study to develop a training process and to refine our audit guide. The resulting 65-page guide serves as both a training tool and reference manual in our full-scale audit. It explains how to assess whether an article meets our criteria for economic uncertainty and economic policy uncertainty and how to code each field in the audit template.[17] The pilot study also led to improvements in the audit process. For example, to ensure that auditor-learning effects are not confounded with differences across papers or over time, the full-scale audit study presents articles to auditors in a randomized order.

To conduct the full-scale audit, we recruited and trained new teams of research assistants. Each new auditor underwent a training process that included a review of the audit guide and template, trial codings of at least 100 articles (not included in the audit sample), a one-on-one meeting to review the trial codings, and additional trial codings and feedback when needed. We met with the audit teams on a weekly basis to address questions, review "hard calls" and coding differences, and maintain esprit de corps. The auditors reviewed 12,009 articles from 1900 to 2012 that we selected using a two-stage approach:[18] First, we specified a target sample size (higher in 1985-2011 and certain key earlier years), and then we randomly sampled a number of articles for each newspaper and month. To monitor audit quality and sharpen incentives for careful work, we randomly assigned about one quarter of the articles to multiple auditors.

Selecting a P term set: When an auditor codes an article as EPU=1, he or she also records the policy terms contained in the passages about economic policy uncertainty. Using these records, we identified 15 terms that appear often in newspaper discussions of EPU from 1985 to

[16] Only 0.5 percent of the articles in our 10 leading newspapers satisfy both the "economy" and "uncertainty" criteria. Thus, the vast majority of all articles read by our auditors would be useless for selecting and evaluating our P term set if we were to sample randomly from all newspaper articles.

[17] The guide includes coding instructions, numerous examples, and FAQs. For example, one of the FAQs asks "Are remarks about uncertain tax revenues grounds for EPU=1?" and answers "Yes, if the article attributes uncertainty about tax revenues partly or entirely to uncertainty about policy choices…. No, if the article attributes uncertainty about tax revenues entirely to uncertainty about economic conditions …" The audit guide is available at www.policyuncertainty.com/Audit_Guide.pptx.

[18] We reviewed more than 15,000 articles across the pre-audit phase, pilot audit, auditor training exercises and full-scale audit, but we draw only on the 12,009 articles in the full-scale audit for our analysis here.

2012: "regulation", "budget", "spending", "policy", "deficit", "tax", "federal reserve", "war", "white house", "house of representatives", "government", "congress", "senate", "president", and "legislation" (and variants like "regulatory", "taxation", etc.). We then considered the approximately 32,000 term-set permutations with four or more of these policy terms. For each permutation, we generated computer assignments of $EPU^C = 0$ or 1 for each article in the sample. By comparing these computer assignments to the human codings, we obtain sets of false negatives ($EPU^C=0$, $EPU^H=1$) and false positives ($EPU^C=1$, $EPU^H=0$) for each permutation. We chose the P term set that minimizes the gross error rate – i.e., the sum of false positive and false negative error rates. This process yields our baseline policy term set for the EPU index in Figure I: "regulation", "deficit", "federal reserve", "white house", "congress", and "legislation".

Appendix Figures B1 to B6 display alternative EPU indices constructed by dropping the six baseline terms, one at a time. Inspecting these figures, it is apparent that the time-series behavior of our EPU index is not particularly sensitive to any single policy term. We also experimented with compound text filters, e.g., adding {government AND tax} to the baseline term set. Somewhat to our surprise, we were unable to develop simple compound text filters that achieved a materially lower gross error rate than our baseline term set.[19]

We repeated this process to obtain the P term set for the historical EPU index in Figure II, which makes use of all six terms in the P set for the modern index plus "tariff" and "war". Adding these two policy terms accords well with the prominent role of tariffs and tariff revenues in the first half of the 20th century and with US participation in World Wars I and II, the Korean War and the Vietnam War, all of which involved much greater per capita rates of US military deployments and casualties than more recent military conflicts.

Time-Series Comparison: We chose the P term set for our computer-automated EPU index to minimize the gross error rate relative to the human benchmark provided by our audit study. To assess the time-series performance implied by our automated classifications, we now compare movements over time in human and computer-generated EPU indices. To do so, we compute the fraction of audit-sample articles with $EPU^H=1$ in each quarter from 1985 to 2012, multiply by the

[19] Our consideration of compound text filters focused on terms that materially lowered the false negative rate when added to the baseline term set – at the cost of even greater increases in the false positive rate. Otherwise, the term in question would be part of the baseline set. "Tax" is the leading example in this regard. As an example of how adding "tax" to the policy term set yields a false positive, see "Credit Markets; Little Change in Treasury Prices" by Kenneth N. Gilpin, *New York Times,* 14 February 1991. The article discusses economic uncertainty and includes remarks about taxable and tax-exempt securities, but it contains no discussion of policy matters.

EU rate for our 10 newspapers, and normalize the resulting human EPU index to 100 over the period. To obtain the corresponding computer EPU index, we instead use the fraction of audit-sample articles with EPU^C=1. Figure V compares these human and computer EPU indices. There are differences between the two series – e.g., a larger spike for the summer 2011 debt-ceiling dispute in the human EPU index – but they are quite similar, with a correlation of 0.86. Repeating the same type of comparison using annual data from 1900 to 2010 in appendix Figure C1, we find a correlation of 0.93 between the human and computer EPU indices.

Figures V and C1 provide some assurance that our computer-automated EPU classifications track the actual time-series variation in the intensity of concerns about EPU, as judged by intelligent human beings. In this regard, it's worth stressing that our term-set selection criterion makes no use of time-series variation. So Figures V and C1 offer something of an independent check on the performance of our automated classification criteria. However, it's also important to understand the limitations of these comparisons. They incorporate our computer-automated EU assignments and, more fundamentally, they rely on the content of newspaper articles. We use other methods, as discussed below, to assess the reliability of newspaper content for the purposes of constructing an EPU index.

For downstream econometric applications, we also care about the time-series properties of the net error rate, given by the difference between the computer and human EPU index values. Calculating this net error rate from the series in Figure V, we find that it is essentially uncorrelated with quarterly real GDP growth rates (correlation of -0.02) and with the "true" (i.e., human) EPU rate in the audit sample (correlation of 0.004).

Other Audit Results: Our audit study also speaks to several other questions related to our EPU index. First, only 5 percent of audit-sample articles with EPU^H=1 mainly discuss actual or prospective declines in policy uncertainty. Apparently, reporters and editors do not regard falling uncertainty as particularly newsworthy. Second, 10 percent of EPU^H=1 articles discuss uncertainty about *who* will make future economic policy decisions, 68 percent discuss uncertainty about *what* economic policies will be undertaken (or *when*), and 47 percent discuss uncertainty about the economic *effects* of past, present or future policy actions. Third, the share of EPU^H=1 articles that discuss *who* will make future economic policy decisions triples in presidential election years, as compared to other years, indicating that the nature of policy uncertainty shifts substantially over the election cycle.[20] Fourth, 32 percent of EPU^H=1 articles mention policy matters in other countries, often alongside domestic policy concerns.

III.B. Political Slant in Newspaper Coverage of EPU

Our audit study does not address the potential for political slant to skew newspaper coverage of EPU. If right-leaning (left-leaning) newspapers seriously overplay EPU when Democrats (Republicans) are in power, political slant could distort measured changes in our index. To investigate this issue, we split our 10 newspapers into the 5 most 'Republican' and 5 most 'Democratic' papers using the media slant index of Gentzkow and Shapiro (2010). They assign slant values based on how frequently newspapers use words preferred by one party or the other in Congressional speech. For example, a newspaper that frequently uses "death tax", "personal accounts" and "war on terror" (terms preferred by Republicans) falls on the right side of their slant index, and a newspaper that frequently uses "estate tax", "private accounts" and "war in Iraq" (terms preferred by Democrats) falls on the left side. Appendix Figure C3 plots the "left" and "right" versions of our EPU index. They move together closely, with a correlation of 0.92. This finding suggests that political slant does not seriously distort variation over time in newspaper coverage of EPU and is not a major concern for our index.

III.C. Comparisons to Other Measures of Uncertainty and Policy Uncertainty

Another way to evaluate our EPU index is by comparison to other measures of uncertainty and policy uncertainty. The most obvious comparator is the VIX, an index of 30-day option-implied volatility in the S&P500 stock index, available since 1990. As seen in Figure VI, the VIX and the EPU index often move together (correlation of 0.58), but they also show distinct variation. For example, the VIX reacts more strongly to the Asian Financial Crisis, the WorldCom Fraud and the Lehman Brothers collapse – events with a strong financial and stock-market connection. In contrast, the EPU index shows stronger responses to war in the Gulf region, the election of a new president, and political battles over taxes and government spending – events that clearly involve major policy concerns but also affect stock market volatility.

[20] We also find electoral cycle effects on the *level* of policy uncertainty in a multi-country setting. In particular, we merge our country-level EPU indices with data on the timing and closeness of democratic national elections from Julio and Yook (2012, 2013), updating their data to cover recent elections. This effort yields an unbalanced panel with 12 countries, 62 national elections (none for China) and 3,263 monthly observations. Using country fixed effects and an election timing indicator as explanatory variables, EPU is on average 16 log points higher during the month of national elections (t-statistic of 5.3, clustering errors at the country level). Including ln(1+|percentage voting gap between first- and second-place finishers|) as an additional regressor, we find statistically significant evidence that close elections yield a further elevation of policy uncertainty – but the closeness effect is small.

Of course, the two measures differ conceptually in several respects. While the VIX reflects implied volatility over a 30-day look-ahead period, our EPU index involves no explicit horizon. The VIX pertains to uncertainty about equity returns, while the EPU index reflects *policy* uncertainty, and not just for equity returns. The VIX covers publicly traded firms only, which account for about one-third of private employment (Davis et al., 2007). To throw some light on the role of these differences, we create a newspaper-based index of equity market uncertainty. Specifically, we retain our E and U term sets but replace the P term set with "stock price", "equity price" or "stock market". The resulting index, shown in appendix Figure C2, correlates with the VIX at 0.73, considerably higher than the EPU-VIX correlation.[21]

This result tells us two things. First, it demonstrates that we can construct a reasonable proxy for an important type of economic uncertainty using frequency counts of newspaper articles – a proof-of-concept for our basic approach. Second, the stronger correlation of the newspaper-based equity index with the VIX confirms that differences in topical scope between the VIX and the EPU index are an important source of distinct variation in the two measures.

Other Text Sources: We also consider uncertainty indicators based on the Beige Book releases before each regularly scheduled meeting of the Federal Open Market Committee (FOMC). The Beige Book, published eight times a year, summarizes in roughly 15,000 words the views and concerns expressed by business and other contacts to the twelve regional Federal Reserve Banks. We count the frequency of "uncertain*" in each Beige Book, normalized to account for variation in word count.[22] We also read each passage that contains "uncertain*" to judge whether it pertains to policy matters and, if so, we record the policy category.

Figure VII shows the resulting quarterly frequency counts per Beige Book (BB). It highlights many of the same shocks and policy developments as the EPU index in Figure I. The quarterly time-series correlation between the EPU index and the BB policy uncertainty indicator is 0.54. The BB policy uncertainty indicator shows little immediate response to the financial crisis but begins to rise in the second half of 2009 and is at highly elevated levels from 2010 to 2013. In a categorical breakdown analogous to Table I (not shown), the Beige Books also point to fiscal policy as the most important source, by far, of elevated policy uncertainty in recent

[21] We make no effort here to develop an optimal term set for the news index of equity market uncertainty, something we are currently pursuing in other work. Instead, Figure C2 reflects our first attempt and can surely be improved.
[22] That is, we divide the raw frequency count by the number of words in the Beige Book and rescale to preserve the average frequency count per Beige Book over the sample period.

years. Financial regulation and sovereign debt concerns figure more prominently in the Beige Books than in newspapers. In contrast to newspapers (but rather unsurprisingly) the Beige Books almost never mention monetary policy uncertainty.

Figure VII also shows a policy uncertainty indicator based on textual analysis of 10-K filings. For each 10-K filing, we count sentences in the Risk Factors section (mandatory since fiscal year 2005) that contain one or more of the policy terms listed in Online Appendix E. We then divide by the total number of sentences in the Risk Factors section and average over firms by year to obtain the series in Figure VII.[23] While the temporal coarseness of the 10-K filings precludes fine-grained comparisons, our analysis reveals a strong upward drift after 2009 in the degree to which firms express concerns about their exposure to policy-related risk factors.[24]

Daily Stock Market Jumps: Finally, following Baker, Bloom and Davis (2015), we characterize all large daily moves (greater than |2.5%|) in the S&P stock index from 1900 to 2012. In each instance, we locate and read the next-day New York Times and Wall Street Journal articles that cover the stock move. We record the explanation(s), according to the article, and classify it as policy-related or not. The idea is that higher policy uncertainty leads to a greater frequency of large equity market moves triggered by policy-related news. As seen in appendix Figure C6, we find precisely that. The correlation of the annual frequency count of daily stock market jumps triggered by policy news and the annual version of the EPU index in Figure II is 0.78. The 1930s and the period during and after the Great Recession stand out in both series.

III.D. Summary

In summary, our audit study and comparison to other text sources and types of data indicate that our newspaper-based EPU indices contain useful information about the extent and nature of economic policy uncertainty. Compared to other policy uncertainty measures, newspaper-based indices offer distinct advantages: They can be extended to many countries and backwards in time, sometimes by a century or more. For large countries like the US, it is feasible

[23] The average length of the Risk Factors section of 10-K filings has grown steadily over time, perhaps because firms are providing increasingly detailed discussions in this regard. For this reason, we prefer to scale by the total number of sentences, so as not to overstate the rising importance of policy-related risk factors.

[24] Appendix Figure C5 reports another 10-K policy uncertainty indicator based on the fact that firms generally discuss risk factors in order of their importance to the firm. Thus, for each 10-K filing, we calculate the percent of the Risk Factors section one must read before encountering a discussion of policy-related risks. Averaging across firms by year, the mean value of this measure falls from 25.2 percent for fiscal year 2005 to 17.0 percent for 2013, and the median falls from 15.2 to 8.7 percent. In other words, the average firm perceives policy risks as increasingly important from 2005 to 2013 relative to other risks.

to construct useful newspaper-based indices at a daily frequency and by region. And newspaper-based indices are readily disaggregated and parsed to develop category-specific indices.

IV. POLICY UNCERTAINTY AND ECONOMIC ACTIVITY

To investigate whether policy uncertainty matters for economic outcomes, we take two complementary approaches. The first uses *firm-level* data, yielding better causal identification but capturing only a limited set of impact channels – government purchases of goods and services and certain aspects of regulatory policy. The second uses *macro data* in VAR analyses, potentially capturing many channels but offering little assurance about the identification of causal effects.

IV.A. Firm-level Outcomes and Policy Uncertainty

Our firm-level analysis considers option-implied stock price volatility, as a proxy for firm-level uncertainty, and investment rates and employment growth as real activity measures. We use US panel data on publicly listed firms and an identification strategy that differentiates firms by exposure to uncertainty about government purchases of goods and services. To measure this exposure, we draw on two sources of information. For firms in Health Services (SIC 80), we use the government share of US healthcare expenditures in 2010, which we calculate as 43.8% in Online Appendix F. For all other industries, we exploit micro data in the Federal Registry of Contracts from 2000 to 2013 as follows.

As a first step, we match the federal contracts database to Compustat firms using DUNS numbers and the names of the parent firm and their US subsidiaries.[25] This match yields the parent firm's revenue derived from Federal contracts, which we allocate to 3-digit SIC industries using industry codes and line-of-business data in Compustat. We then aggregate revenues and contract awards to obtain the ratio of federal purchases to revenues in each 3-digit industry by year. To smooth out high-frequency variation from lumpy contract awards, we average these ratios from 2000 to 2013 to obtain our exposure measure for each 3-digit SIC. At the top end, firms operating in the Guided Missiles and Space Vehicles and Parts Industry (SIC 376) derive

[25] We do so using Dunn & Bradstreet's US database of all public and private firms, which includes a firm name, DUNS number, industry and ownership information. In this way, we capture federal contracts of the publicly listed parent firm (e.g. "General Electric") ***and*** contracts with subsidiaries of the parent firm (e.g. "General Electric Capital Services" and "USA Instruments").

78% of their revenues (in SIC 376) from sales to the federal government. The corresponding figure for selected other industries with high exposures to federal purchases is 39% for Ordnance and Accessories (SIC 348), 27% for Search, Detection, Navigation, Guidance & Aeronautical Systems (SIC 381), 21% for Engineering Services (SIC 871), 20% for Aircrafts and Parts (SIC 372), 15% for Ship and Boat Building and Repairing (SIC 373), 11% for Blank Books, Loose Leaf Binders, and Bookbinding (SIC 278), and 9% for Heavy Construction (SIC 160). Direct sales to the federal government are comparatively small in most other industries.

In a second step, we measure each firm's exposure to government purchases as its revenue-weighted mean (across its lines of business) of the industry-level exposure measures calculated in the first step. If the firm operates in a single 3-digit SIC, then its exposure measure equals the corresponding industry exposure measure. We prefer this two-step approach because it may lessen the scope for reverse causality, and because industry-level measures may better proxy for the firm's ex ante exposure to uncertainty about government purchases. Our robustness investigations below consider several other firm-level policy exposure measures.

IV.B. Implied Stock Price Volatility

Table II displays results from regressing firms' 30-day implied stock-price volatility on economic policy uncertainty. We obtain the implied volatility measure from Options Metrics, which calculates the 30-day volatility implied by firm-level equity options. These options have been traded since the mid-1990s on the Chicago Board of Options and Exchange (CBOE, 2014), and our data begin in 1996. We use this volatility measure in quarterly regressions to match the quarterly company accounts, averaging implied volatility over all trading days in the quarter. We run regressions on a sample that extends from 1996 to 2012 and weight by firm sales, giving more weight to the larger firms that also tend to have more actively traded equity options.

Column (1) reports a very basic specification that regresses logged 30-day implied volatility on our EPU index and the ratio of federal government purchases to GDP, a control for the first moment of policy. Log(EPU) is highly statistically significant, with the coefficient of 0.432 indicating that a 1% EPU increase is associated with a roughly 0.43% increase in firm-level implied volatility. To put this magnitude in perspective, our EPU index rose by 85.6 log points (135%) from 2006 to 2012, which implies an estimated upward shift of 37 log points (45%) in average firm-level implied volatility. The negative coefficient on the control variable in

Column (1) says that, conditional on log(EPU), average firm-level implied volatility is lower when the ratio of federal purchases to GDP is higher.

Column (2) contains the key result. We add a full set of firm and time fixed effects to control for unobserved factors that differ across firms and unobserved common factors that vary over time. The log(EPU) and Federal Purchases/GDP terms drop out, as they are collinear with the time effects. But we now interact these measures with our firm-level measures of exposure to government purchases. This specification tests whether implied volatility at firms with greater exposure to government purchases co-varies more strongly with policy uncertainty. We find very strong evidence for this. The coefficient of 0.215 on the log(EPU)*Intensity measure suggests that for every 1% increase in our policy uncertainty index a firm with, say, a 50% government revenue share would see its stock volatility rise by 0.11%.[26]

Column (3) evaluates to what extent our EPU measure tells us anything different from the VIX index, the most commonly used proxy for overall economic uncertainty. As noted in Section III.C, our EPU index and the VIX have a correlation coefficient of 0.58. Adding the VIX in a specification without firm or time effects reverses the sign of the EPU term, while the coefficient on the VIX is large (at 0.734) and highly significant. This result is unsurprising since the VIX is the 30-day implied volatility on the S&P500 index, and it should be highly correlated with the average 30-day implied volatility for publicly listed US firms.

Column (4) again adds time and firm fixed effects, and we now interact the EPU, Federal Purchases/GDP and VIX measures with the intensity of the firm's exposure to government purchases. Strikingly, we now find that the EPU index has a large and significant coefficient, while the VIX drops out entirely. Combining columns (3) and (4) reveals that the 30-day implied volatility is best explained by the VIX index for the average firm, but the EPU index provides additional explanatory power for the implied volatility of firms in sectors with high government exposure – like defense, healthcare, engineering services and heavy construction.

Columns (5) and (6) run a similar evaluation for the Economic Uncertainty (EU) index, yielding similar results. In column (5) we run a regression with the EPU, EU and Federal Purchases/GDP measures, but no time or firm fixed effects. The EU index dominates with a large and highly significant coefficient. Again, this result is not surprising – the EU index

[26] Using a quite different empirical design and source of variation, Kelly, Pastor and Veronesi (2016) find evidence that policy uncertainty related to election outcomes also raises option-implied stock market volatility.

reflects the overall frequency of newspaper articles about economic uncertainty, without any stipulation that these articles also discuss policy. Column (6) adds time and firm fixed effects, and we again interact the key measures with each firm's exposure to government purchases. As before, the EPU measure dominates the general uncertainty measure in the interacted specification with controls for firm and time effects. Indeed, the EU measure now takes on the opposite sign. In summary, while the EU index is more closely related to the average firm-level implied volatility in the specification (5) that excludes firm and time effects, the EPU index outperforms the EU index in explaining firm-specific movements in option-implied volatility.

Finally, in column (7) we add category-specific EPU measures from Section II.B for firms in the defense, finance and healthcare sectors. These category-specific measures potentially capture a broad range of impact channels, including ones that involve regulatory policy. Reassuringly, all three of these measures yield positive, statistically significant coefficients at the 1 to 10 percent level. For example, implied volatility for defense firms responds to the National Security EPU index, which jumped up in Gulf Wars I and II and after the 9/11 terrorist attacks (Figure III). Similarly, implied volatility for firms in the healthcare sector responds to the Healthcare EPU index, which rose during the Clinton healthcare reform initiative and in response to uncertainties surrounding the Affordable Care Act. The large, highly significant coefficient on the Financial Regulation EPU index is especially noteworthy, because direct federal purchases of goods and services are miniscule in the finance sector. Thus, we see this result as evidence that regulatory policy uncertainty drives firm-level stock price volatility.

These results imply that policy uncertainty accounts for significant variation in the cross-sectional structure of stock-price volatilities. To see this point, consider the estimated changes in firm-level volatilities associated with the change in policy uncertainty from 2006 to 2012. Using the results in Table II Column (7), we calculate these changes as (0.082)*(firm's exposure to government purchases)*(change in overall log EPU) plus (coefficient on category-specific log EPU)*(change in category-specific log EPU). Appendix Table A.1 implements this calculation for firms in selected industries, yielding increases of up to 23.8 log points for financial firms and 13.9 log points for healthcare firms, mainly due to the run up in their respective category-specific EPU indices; and 3.3 to 4.6 log points for firms in the Ordnance, Aircraft and Engineering Services industries, mainly due to their strong exposures to government purchases and the rise in overall policy uncertainty. Comparing July-August 2001 to September-October 2001 (before and after 9-11) and carrying out the same type of calculations, we find stock-price volatility increases of 14-15 log points for firms in Ordnance, Aircraft and Engineering Services, 11.2 log points in Finance sector, 7.5 log points in Healthcare, and tiny responses for firms in most other industries. Hence, the implied magnitudes are sizable for firms in industries with large policy exposures.

Table III presents a wide range of additional robustness results for specifications that include firm and year fixed effects. Columns (1) and (2) consider realized volatility and 182-day implied volatility to look at longer and shorter uncertainty horizons, yielding very similar results. Column (3) adds forecasts from the Survey of Professional Forecasters of government purchases relative to GDP (interacted with firm-level exposure) as a control, and Column (4) uses actual future government purchases relative to GDP (again interacted) as a control. Column (5) replaces our preferred firm-level exposure measure (calculated by the two-step method described above) with a one-step measure calculated directly from the firm's own sales to the federal government. Column (6) uses the Belo et al. (2013) measure of industry-level exposure to government purchases, which exploits the input-output matrix to capture direct and indirect effects of government purchases.

Columns (7) and (8) in Table III consider two entirely different approaches to measuring firm-level exposure to government policy risks. In column (7), we measure exposure by the slope coefficient in a regression of the firm's daily stock returns on our daily EPU index from 1985 to 1995, which pre-dates the sample period in Table II. Using this "beta" measure of policy risk exposure, we again find positive and statistically significant effects of EPU on firm-level volatility. In Column (8), we use the policy risk exposure measure derived from 10-K filings and plotted over time in Figure VII, but now measured at the firm level (averaging over available years). We again find sizable effects of EPU on firm-level volatility, but the coefficient on the log(EPU) interaction term is less statistically significant, partly due to a smaller sample size[27] and perhaps partly because this measure reflects the firm's perceived exposure to policy risk factors from 2006 onwards only, whereas the regression sample starts in 1996. Column (9)

[27] The sample shrinks for several reasons. First, the SEC did not mandate a Risk Factors discussion before 2006, so we cannot obtain this measure for firms that delisted before 2006. Second, some publicly listed firms are exempt from the Risk Factors disclosure requirement, and some may not comply. Third, our web-scraping and automated text-reading methods may not capture all relevant 10-K filings, perhaps because some firms present their discussion of Risk Factors in an unusual format. Fourth, it is not always possible to match data from 10-K filings to Compustat. Our match rates compare favorably to similar efforts by other researchers. See Online Appendix E for additional discussion.

restricts attention to firms with at least \$500 million in annual sales. These alternative measures and specifications all yield highly significant results similar to Column (2) in Table II.

Finally, appendix Table A.2 returns to the baseline specification in Table II Column (2) and replaces the key log(EPU) interaction term by log(EPU/X), where X corresponds to the newspaper-based E ("Economy"), P ("Policy"), U ("Uncertainty), EP, EU or PU index. These variants yield slope coefficients on the key log(EPU/X)*intensity variable that are statistically indistinguishable from the point estimate in Table II Column (2). This highlights how it is the triple combination of the E, P and U term sets in newspaper articles that drive our results rather than the frequency of the individual E, P or U term sets or the precise scaling of the EPU index.

IV.C. Investment Rates and Employment Growth

Table IV investigates the contemporaneous relationship between policy uncertainty and firm-level investment rates and employment growth.[28] We now have data from 1985 to 2012 and, as before, weight by firm sales. We use our preferred measure of the firm's policy exposure intensity and a full set of time and firm effects in all Table IV specifications. Column (1) reports a regression of the firm-level quarterly investment rate on $\Delta\left(\log(\text{EPU})\right) * \text{Intensity}$ and $\Delta\left(\text{Federal Purchases/GDP}\right) * \text{Intensity}$. The former has a significant negative coefficient of -0.032, and the latter has a significant positive coefficient. These results are in line with standard predictions of investment-under-uncertainty models, e.g., Bernanke (1983), Dixit and Pindyck (1994) and Bloom, Bond and Van Reenen (2007).

To assess the magnitude of the estimated policy uncertainty relationship, recall that the EPU index rose 85.6 log points from 2006 to 2012. For a firm that sells 25% of its output to the federal government, this EPU change and the coefficient on Δ log(EPU)*Intensity in Column (1) imply a one-time investment rate drop of 0.68 percentage points (=0.856*0.032*0.25*100), which is about one-sixth of the median firm-level investment rate of 4.2 percent. While this calculation rests on a large EPU swing, there were several other large EPU moves during the sample period – e.g., a fall of 82 log points from 1992 to 1999, a 72 point rise from 1999 to 2001, and a 79 point fall from 2001 to 2006. Hence, for firms with high exposures to government

[28] We focus on simple linear specifications that do not allow for rich response dynamics or interactions between uncertainty and the responsiveness of outcome variables to first-moment driving forces. More sophisticated treatments of investment behavior in these respects using other measures of uncertainty include Abel and Eberly (1996), Guiso and Parigi (1999) and Bloom, Bond and Van Reenen (2007). There is value in applying these more sophisticated treatments to our policy uncertainty measures, but we leave that task to future research. For a richer treatment of dynamics in firm-level investment rate responses to our EPU measure, see Gulen and Ion (2016).

purchases, the estimates imply that swings in policy uncertainty involve material changes in investment rates.

In column (2) we control for $\Delta(\text{Forecasted Federal Purchases/GDP})*\text{Intensity}$, given the forward-looking nature of investment decisions, and obtain very similar results on the main coefficient of interest. Adding controls for cash flow and Tobin's q in column (2) yields a coefficient of 0.30 (0.10) on $\Delta(\log(\text{EPU}))*\text{Intensity}$, again very similar to column (1).[29] In column (3) we include the average $\Delta(\text{Federal Purchases/GDP})*\text{Intensity}$ value in the next 12 quarters as an alternative control for future expectations, and again find a significant negative coefficient. In column (4) we add the category-specific measures and find statistically significant negative results for terms involving log changes in the Healthcare EPU index and the Financial Regulation EPU index. That is, the frequency of newspaper articles about these types of policy uncertainty has additional explanatory power for the investment rates of firms that operate in sectors most affected by these types of policy.

Columns (5) to (8) regress annual firm-level employment growth rates on EPU (Compustat lacks quarterly employment data.) As with investment rates, we find sizable and statistically significant negative coefficients on policy uncertainty for employment growth rates at firms with high exposure to government policy. Consider again an 85.6 log point increase in the EPU index and a firm that sells 25% of its output to the federal government. Given these values, the coefficient of -0.213 on $\Delta(\log(\text{EPU}))*\text{Intensity}$ in Column (5) implies a one-time drop in the annual employment growth rate of 4.6 percentage points, which is large relative to the mean annual growth rate of 3.4 percent for firms in the sample. The category-specific EPU variables do not have statistically significant effects on employment growth, in contrast to the investment results.

In column (9) we consider the impact on sales as a placebo test. While the real-options literature highlights how uncertainty suppresses demand for *input factors* with adjustment costs – the short-run impact on *output* should be smaller according to this class of theories. Consistent with this prediction, the estimated effect of $\Delta(\log(\text{EPU}))*\text{Intensity}$ in column (9) is negative but

[29] Using Compustat data, our cash flow measure is operating income before depreciation expressed as a ratio to the book value of plant, property and equipment. The numerator of our Tobin's q measure is the market value of equity (common and preferred shares) plus the book value of debt less the value of inventories and deferred tax credits, and the denominator is the book value of plant, property and equipment.

not statistically significant, while the government purchases variable remains positive and significant. Hence, our results suggest that increases in policy uncertainty are associated with contemporaneous drops in investment rates and employment growth rates for firms in policy-exposed sectors, but the near-term association with their output growth rates is more muted.

Finally, consider the relationship of policy uncertainty changes to the cross-sectional structure of investment rates and employment growth. To do so, we return to Table A.1 and carry out calculations that parallel the earlier ones for stock-price volatility. Working again with the policy uncertainty changes from 2006 to 2012, the implied quarterly investment rate changes are modest except for a 2.9 percent drop for firms in the Healthcare sector, while the annual employment changes are large in several sectors. Given the change-on-change nature of the underlying regression specifications, these results are one-time changes associated with the total change in the policy uncertainty measures from 2006 to 2012.

IV.D. Policy Uncertainty and Aggregate Economic Activity

We now turn to VAR models that exploit time-series variation at the country level. Drawing causal inferences from VARs is extremely challenging – in part because policy, and policy uncertainty, can respond to current and anticipated future economic conditions. Despite the challenges, VARs are useful for characterizing dynamic relationships. At a minimum, they let us gauge whether policy uncertainty innovations foreshadow weaker macroeconomic performance conditional on standard macro and policy variables.

We start by fitting a VAR to monthly US data from January 1985 to December 2014. To recover orthogonal shocks, we use a Cholesky decomposition with the following ordering: the EPU index, the log of the S&P 500 index, the federal funds rate, log employment, and log industrial production. Our baseline VAR specification includes three lags of all variables. Figure VIII depicts the model-implied responses of industrial production and employment to a 90-point upward EPU innovation, equal in size to the EPU change from its average value in 2005-06 (before the financial crisis and recession) to its average value in 2011-12 (a period with major fiscal policy battles and high EPU levels). Figure VIII shows maximum estimated drops of 1.1% in industrial production and 0.35% in employment. These responses are statistically significant and moderate in size, being about one-third as large as a typical business cycle fluctuation. Since aggregate US investment data are not available at a monthly frequency, we also estimated an analogous VAR model on quarterly data from 1985 to 2014, using the same type of Cholesky decomposition to identify shocks. As shown in appendix Figure C7, gross aggregate investment exhibits a peak decline of about 6% in response to a 90-point EPU innovation.

Figure IX shows that the basic character of the impulse response functions is robust to several modifications of the specification, variable set, causal ordering and sample period: six lags instead of three in the VAR, a bivariate VAR (EPU and industrial production), a bivariate VAR with reverse ordering, including the VIX (after the EPU index), including the EU index (after the EPU index), dropping the S&P500 index, including time trends, and using a sample period that runs from 1920 (when industrial production data become available) until 1984. These results are in line with the estimated effects of election uncertainty in Julio and Yook (2012) and Durnev (2010), despite their distinct empirical approaches.

A potential concern is whether, and to what extent, our estimated impulse response functions reflect bad news generally rather than policy uncertainty shocks in particular. Including the S&P500 stock market index in the VAR somewhat mitigates this concern, given that stock markets are forward looking and that stock prices incorporate many sources of information. Our baseline VAR also includes other "first-moment" variables: log employment, log industrial production, and the fed funds rate. Still, the EPU index will likely embed first-moment information not captured by these variables. To investigate this issue, we also considered VARs that include the Michigan Consumer Sentiment Index.[30] When we place the Michigan index after the EPU index in the causal ordering, the estimated peak effect of a policy uncertainty shock on industrial production falls by about one-third (appendix Figure C8). When we place the Michigan index first in the causal ordering, the peak effect shrinks by about half. These results indicate that, conditional on the other variables, our EPU index and the Michigan index contain overlapping information that has value for predicting future output and employment movements.

Perhaps this result is unsurprising. The Michigan index captures a mix of first-moment and second-moment concerns, as expressed by households in survey data. The relationship between "confidence" and uncertainty is a murky one, and the two concepts are tightly linked at

[30] The Michigan index reflects phone surveys of consumers and seeks to determine how consumers view the short-term economy, the long-term economy, and their own financial situation. It takes the difference between the percent answering positively and the percent answering negatively for each of 5 questions, then averages these differences and normalizes by the base period (December 1968) total. The Michigan index has a correlation of -0.742 with our EPU index. We chose the Michigan index as the more commonly used consumer confidence index, but other consumer confidence indices are highly correlated with the Michigan Index – for example, the Bloomberg Confidence index has a correlation of 0.943 with the Michigan index, and the Conference Board Confidence index has a correlation of 0.912 with the Michigan index.

a deep level in some theoretical models, e.g., Ilut and Schneider (2014). In any event, the EPU index has several important advantages relative to consumer confidence indices: EPU indices can be extended to many countries, pushed back in time by a century or more in some countries, computed in near real-time on a daily basis, and parsed in many ways as illustrated by our category-specific EPU indices.

Figure X shows impulse response functions for a panel VAR fit to monthly data from 1985 to 2014 on the twelve countries for which we have an EPU index. The panel VAR specification parallels the baseline specification that underlies Figure VI, except that we use the unemployment rate in place of log(employment). As before, we rely on a Cholesky decomposition to identify shocks and display responses to an upward 90-point EPU innovation, which is well within the range of EPU movements experienced by the individual countries. The twelve-country panel VAR yields results that are similar to the US results in Figure VIII. In particular, the international panel VAR implies that a 90-point EPU innovation foreshadows a peak drop in industrial production of about 1 percent and a rise in the unemployment rate of about 25 basis points. Appendix Figure C9 shows that the basic character of the panel VAR results is robust to a variety of alternative specifications, variable sets, and weighting methods. Other researchers who use our EPU indices in multi-country time-series analyses also find that policy uncertainty shocks foreshadow deteriorations in macroeconomic outcomes – examples include the IMF (2013), Columbo (2013), Klössner and Sekkel (2014) and Nodari (2014).

Broadly speaking, we see three ways to interpret this VAR-based evidence. Under the first interpretation, an upward EPU innovation corresponds to an unforeseen policy uncertainty shock that causes the worsening of macroeconomic performance through real options effects, cost-of-capital effects or other mechanisms. Second, an upward EPU innovation captures bad news about the economic outlook that is not (fully) captured by the other variables in the VAR system, *and* that bad news triggers a rise in EPU that has harmful effects on the economy. Under this interpretation, EPU amplifies and propagates a causal impulse that originates elsewhere. Third, EPU has no role as either an impulse or a propagation mechanism; instead, it simply acts as a useful summary statistic for information missing from the other variables in our system — log(output), log(employment) or unemployment, the policy rate, log(S&P 500), the VIX, and consumer sentiment.[31] This third interpretation is hard to fully reconcile with our firm-level results, which suggests that policy uncertainty has negative causal effects. It's also worth noting that our VAR results may understate the importance of policy uncertainty shocks as a driving force, even under the first interpretation, because other variables in the VAR system may respond to news about future policy uncertainty shocks before they show up in the EPU measure.

Clearly, there is a need to develop a robust identification strategy for assessing the causal role of policy uncertainty in macroeconomic performance by, for example, exploiting close, consequential democratic elections and exogenous sources of variation in policy uncertainty such as shifts in the outlook for conflict between North and South Korea or events like the UK "Brexit" vote regarding participation in the European Union. In addition, linear VAR systems may be overly restrictive in how they model EPU responses to other shocks. Perhaps EPU rises in the wake of large negative shocks but responds relatively little to small ones. Allowing for this type of asymmetry may lead to a larger role for EPU in amplifying and propagating the effects of large negative shocks. It would also be useful to consider stochastic volatility models that allow EPU shocks to directly influence the future volatility of other shocks, including shocks to policy variables. We leave these tasks to future research.

At a deeper level, the causal role of policy uncertainty is potentially quite subtle. Sound institutions and policy regimes foster predictable policy responses, even in the face of large negative shocks. In this way, good institutions and policy regimes lessen the scope for policy to act as a source of uncertainty impulses or, through uncertain policy responses, to amplify and propagate the effects of other shocks.

V. CONCLUSION

We develop new measures of economic policy uncertainty for the United States and eleven other major economies. We use these new measures to investigate the relationship of policy uncertainty to firm-level stock-price volatility, investment rates and employment growth and to aggregate investment, output and employment. Our findings are broadly consistent with theories that highlight negative economic effects of uncertainty shocks. The results suggest that elevated policy uncertainty in the United States and Europe in recent years may have harmed

[31] Stock and Watson (2012) consider many more variables in much larger and richer time-series models. They still find evidence that EPU innovations precede deteriorations in aggregate performance.

macroeconomic performance. They also point to sizable effects of policy uncertainty on the cross-sectional structure of stock-price volatilities, investment rates and employment growth.

From a methodological perspective, we show how to tap newspaper archives to develop and evaluate new measures of interest to macroeconomists, financial economists, economic historians and other researchers. In this regard, it's worth stressing that newspapers are available for countries around the world, and they have circulated in similar form for decades in most countries and for centuries in some countries. This ubiquity, coupled with modern databases and computers, offers tremendous possibilities for drawing on newspaper archives to deepen our understanding of broad economic, political and historical developments through systematic empirical inquiries.

Kellogg School of Management
Stanford University, CEPR, SIEPR and NBER
Chicago Booth School of Business, NBER

References

Abel, Andrew, "Optimal investment under uncertainty," *American Economic Review*, 73, no. 1 (1982), 228–233.

Abel, Andrew and Janice Eberly, "Optimal investment with costly reversibility*," Review of Economic Studies,* 63, no. 4 (1996), 581–593.

Alexopoulos, Michelle and Jon Cohen, "The Power of Print: Uncertainty Shocks, Markets, and the Economy," *International Review of Economics and Finance,* 40 (2015), 8-28.

Azzimonti, Marina, "Partisan Conflict and Private Investment," NBER Working Paper 21723 (2015).

Bachmann, Rüdiger, Steffen Elstener, and Eric Sims, "Uncertainty and Economic Activity: Evidence from Business Survey Data," *American Economic Journal: Macroeconomics,* 5, no. 2 (2013), 217-249.

Baker, Scott, Nicholas Bloom, Brandice Canes-Wrone, Steven J. Davis and Jonathan Rodden, "Why Has US Policy Uncertainty Risen Since 1960?" *American Economic Review, Papers & Proceedings,* 104, no. 5 (2014), 56-60.

Baker, Scott, Nicholas Bloom and Steve J. Davis, "What triggers stock market jumps?" Work in progress presented at the January 2015 ASSA meetings (2015).

Basu, Susanto and Brent Bundick, "Uncertainty shocks in a model of effective demand," NBER working paper 18420, (2014).

Belo, Federico, Vito D. Gala and Jun Li, "Government Spending, Political Cycles, and the Cross Section of Stock Returns," *Journal of Financial Economics,* 107, no 2 (2013), 305-324.

Bernanke, Ben S., "Irreversibility, Uncertainty and Cyclical Investment," *Quarterly Journal of Economics*, 97, no. 1 (1983), 85–106.

Bloom, Nicholas, "The Impact of Uncertainty Shocks," *Econometrica,* 77 no. 3 (2009), 623-685.

Bloom, Nicholas, "Fluctuations in Uncertainty," *Journal of Economic Perspectives*, 28, no. 2 (2014), 153-176.

Bloom, Nicholas, Stephen Bond, and John van Reenen, "Uncertainty and Investment Dynamics," *Review of Economic Studies,* 74 (2007), 391-415.

Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta and Stephen Terry, "Really Uncertain Business Cycles," working paper, Stanford (2014).

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

Boudoukh, Jacob, Ronen Feldman, Shimon Kogan, and Matthew Richardson, "Which News Moves Stock Prices? A Textual Analysis" NBER Working Paper 18725 (2013).

Brogaard, Jonathan and Andrew Detzel, "The Asset Pricing Implications of Government Economic Policy Uncertainty," *Management Science,* 61, no. 1 (2015), 3-18.

Campbell, John L., Hsinchun Chen, Dan S. Dhaliwal, Hsin-min Lu and Logan B. Steele, "The Information Content of Mandatory Risk Factor Disclosures in Corporate Filings," *Review of Accounting Studies,* 19, (2014), 396-455.

Chicago Board Options Exchange, "VIX CBOE Volatility Index," White Paper (2004).

Colombo, Valentina, "Economic Policy Uncertainty in the US: Does It Matter for the Euro Area?" *Economics Letters,* 121, no. 1 (2013), 39-42.

Davis, Steven J., John Haltiwanger, Ron Jarmin and Javier Miranda, "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms," *NBER Macroeconomics Annual,* 21, (2007), 107-180.

Dixit, Avinash K. and Robert S. Pindyck, *Investment Under Uncertainty*. Princeton, NJ: Princeton University Press (1994)

Durnev, Art, "The Real Effects of Political Uncertainty: Elections and Investment Sensitivity to Stock Prices," working paper, McGill University, September (2010).

Fernandez-Villaverde, Jesus, Pablo Guerron-Quintana, Keith Kuester, and Juan Rubio-Ramirez, "Fiscal volatility shocks and economic activity," *American Economic Review,* 105, no. 11 (2015), 3352-3384.

Friedman, Milton, "The Role of Monetary Policy," *American Economic Review*, 58, no. 1 (1968), 1-17.

Federal Open Market Committee, Minutes of the December (2009) Meeting, http://www.federalreserve.gov/monetarypolicy/fomcminutes20091216.htm.

Gentzkow, Matthew and Jesse M. Shapiro, "What Drives Media Slant? Evidence from US Daily Newspapers," *Econometrica* 78, no. 1 (2010), 35-71.

Giavazzi, Francesco and Michael McMahon, "Policy Uncertainty and Household Savings," *Review of Economics & Statistics,* 94, no. 2 (2012), 517-531.

Gilchrist, Simon, Jae W. Sim and Egon Zakrajsek, "Uncertainty, Financial Frictions, and Investment Dynamics," NBER Working Paper 20038 (2014).

Guiso, Luigi and Guiso Parigi, "Investment and demand uncertainty," *Quarterly Journal of Economics,* 114, no. 1 (1999),185-227.

Gulen, Huseyin and Mihai Ion, "Policy uncertainty and corporate investment," *Review of Financial Studies,* 29, no. 3 (2016), 523-564.

Handley, Kyle and Nuno Limao, "Trade and Investment under Policy Uncertainty: Theory and Firm Evidence," *American Economic Journal: Policy,* 7, no. 4 (2015), 189-222.

Hartman, Richard, "The effects of price and cost uncertainty on investment," *Journal of Economic Theory,* 5, no. 2 (1972), 258 – 266.

Hassett, Kevin A. and Gilbert E. Metcalf, "Investment with Uncertain Tax Policy: Does Random Tax Policy Discourage Investment?" *Economic Journal,* 109, no. 457 (1999), 372-393.

Higgs, Robert, "Regime Uncertainty: Why the Great Depression Lasted So Long and Why Prosperity Resumed After the War," *The Independent Review*, 1, no. 4 (1997), 561-590.

Hoberg, Gerard, and Gordon Phillips, "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis." *Review of Financial Studies,* 23, no. 10 (2010), 3773–3811.

Ilut, Cosmin and Martin Schneider, "Ambiguous Business Cycles," *American Economic Review,* 104, no. 8 (2014), 2368-2399

International Monetary Fund. "World Economic Outlook: Coping with High Debt and Sluggish Growth," October, IMF Press (2012).

International Monetary Fund, "World Economic Outlook: Hopes, Realities, Risks," April, IMF Press (2013).

Julio, Brandon and Youngsuk Yook, "Political Uncertainty and Corporate Investment Cycles," *Journal of Finance,* 67, no. 1 (2012), 45-83.

Julio, Brandon and Youngsuk Yook, "Policy Uncertainty, Irreversibility, and Cross-Border Flows of Capital," Finance and Economics Discussion Series, Federal Reserve Board, (2013).

Jurado, Kyle, Ludvigson, Sydney and Ng, Serena, "Measuring Uncertainty," *American Economic Review,* 105, no.3 (2015), 1177-1216.

Kelly, Bryan, Lubos Pastor and Pietro Veronesi, "The Price of Political Uncertainty: Theory and Evidence from the Option Market," *Journal of Finance,* forthcoming (2016).

Klössner, Stefan and Rodrigo Sekkel, "International Spillovers of Policy Uncertainty," *Economics Letters,* 124, no. 3 (2014), 508-512.

Koijen, Ralph S.J., Tomas J. Philipson and Harald Uhlig, "Financial Health Economics," *Econometrica,* 84, no. 1 (2016), 195-242.

Leduc, Sylvain and Zheng Liu, "Uncertainty Shocks Are Aggregate Demand Shocks," Federal Reserve Bank of San Francisco working paper, May (2015).

Nalewaik, Jeremy, "Regime-Switching Models for Estimating Inflation Uncertainty," working paper, Board of Governors of the Federal Reserve System, August (2015).

Nodari, Gabriela, "Financial Regulation Policy Uncertainty and Credit Spreads in the United States," *Journal of Macroeconomics,* 41 (2014), 122-132.

Oi, Walter, "The desirability of price instability under perfect competition," *Econometrica* 29, no. 1 (1961), 58–64.

Panousi, Vasia and Dimitris Papanikolaou, "Investment, idiosyncratic risk and ownership," *Journal of Finance*, 67, no. 3 (2012), 1113-1148.

Pastor, Lubos and Pietro Veronesi, "Uncertainty about Government Policy and Stock Prices," *Journal of Finance,* 67, no. 4 (2012), 1219-1264.

Pastor, Lubos and Veronesi, Pietro, "Political Uncertainty and Risk Premia," *Journal of Financial Economics,* 110, no. 3 (2013), 520-545.

Rodrik, Dani, "Policy Uncertainty and Private Investment," *Journal of Development Economics,* 36, no. 2 (1991), 229-242.

Scotti, Chiara, "Surprise and Uncertainty Indexes: Real-Time Aggregation of Real-Activity Macro Surprises," working paper, Federal Reserve Board, (2014).

Shoag, Daniel and Stan Veuger, "Uncertainty and the Geography of the Great Recession," AEI Economic Policy Working Paper 2015-07, (2015).

Stock, James and Mark Watson, "Disentangling the Channels of the 2007-2009 Recession," *Brookings Panel on Economic Activity,* Spring, 81-135, (2012).

Table I
Economic Policy Uncertainty by Policy Category and Time Period, 1985 to 2014

Time period	1985:1-1990:6	1990:7-1991:12	1992:1-2001:8	2001:9-2002:12	2003:1 – 2007:6	2007:7-2008:8	2008:9-2009:12	2010:1-2013:10	1985:1-2014:12
	Mid 80s to Gulf War I	Gulf War I	1990s boom to 9/11	9/11 attacks	2000s boom	Early Credit Crunch	Lehman collapse & recession	Fiscal Policy Battles	Overall Average
Overall Economic Uncertainty	218.2	349.8	185.9	326.9	159.8	184.8	370.9	252.1	219.3
Economic Policy Uncertainty	109.6	141.9	88.1	128.5	71.4	83.4	132.1	127.5	100.0
Fiscal Policy	49.6	59.6	35.9	55.4	32.3	33.1	61.5	78.3	46.1
- Taxes	39.9	48.4	31.9	51.2	30.2	31.4	56.9	68.1	40.3
- Government Spending & Other	22.7	26.8	12.1	17.3	8.5	6.6	17.1	33.2	17.1
Monetary Policy	32.7	41.8	26.1	45.2	22.2	31.6	27.8	26.1	28.1
Healthcare	7.0	15.4	14.9	18.4	13.1	13.4	29.3	39.3	17.3
National Security	25.0	53.6	18.0	54.8	25.4	15.9	21.3	19.8	23.8
Regulation	15.7	23.0	14.5	19.6	11.2	15.5	29.2	28.1	17.4
- Financial Regulation	3.3	7.0	1.3	5.3	1.7	3.6	10.2	6.1	3.3
Sovereign Debt & Currency Crises	1.4	0.6	2.3	0.5	0.4	0.3	0.4	3.9	1.6
Entitlement Programs	7.3	12.6	11.5	18.7	8.8	8.2	15.3	24.7	12.4
Trade Policy	3.8	4.0	6.3	2.6	1.7	2.0	1.4	2.1	3.8
Sum of Policy Categories	142.5	210.7	129.5	215.1	115.2	120.0	186.3	222.2	150.6
Ratio of EPU To Overall EU	0.50	0.41	0.47	0.39	0.45	0.45	0.36	0.51	0.47

Notes: Queries run 12 February 2015 on US newspapers in Access World News Newsbank, using the category-specific policy term sets listed in Online Appendix B. Except for the last row, all entries are expressed relative to the average EPU frequency from 1985 to 2014. "Overall Economic Uncertainty" quantifies the frequency of articles that meet our "economy" and "uncertainty" requirements (i.e., dropping the "policy" requirement) and is also expressed relative to the average EPU frequency from 1985 to 2014. The category-specific index values sum to more than 100 for two reasons: First, we use a few policy terms in more than one policy category. For example, "Medicaid" appears in the term sets for both Healthcare and Entitlement Programs. Second, a newspaper article that meets the "economy", "policy" and "uncertainty" criteria can refer to more than one policy category.

Table II
Option-Implied Stock Price Volatility and Policy Uncertainty

Dep Var: Log(30-day implied vol)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Log(EPU)	0.432***		-0.044***		-0.752***		
	(0.010)		(0.013)		(0.027)		
Log(EPU)×Intensity		0.215**		0.228**		0.545***	0.082
		(0.069)		(0.100)		(0.202)	(0.117)
Log(VIX)			0.734***				
			(0.016)				
Log(VIX)×Intensity				-0.020			
				(0.117)			
Log(EU)					1.080***		
					(0.027)		
Log(EU)×Intensity						-0.301**	
						(0.177)	
Federal Purchases/GDP	-19.30***		-7.75***		-17.40***		
	(1.50)		(1.49)		(1.49)		
(Federal Purchases/GDP)× Intensity		-29.45*		-29.70**		-29.93*	-31.08
		(12.72)		(12.36)		(12.66)	(13.24)
National Security EPU*Defense							0.048***
							(0.012)
Healthcare EPU*Health							0.071*
							(0.043)
Financial Regulation EPU*Finance							0.144***
							(0.030)
Firm and Time Effects	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**Yes**

Notes: The sample contains 136,578 observations on 5,460 firms from 1996 to 2012. The dependent variable is the natural log of the 30-day implied volatility for the firm, averaged over all days in the quarter. **Intensity** is the firm's exposure to federal purchases of goods and services computed by the two-step method described in Section IV. **Federal Purchases/GDP** is from NIPA tables. **Log(EU)** is the log of the newspaper-based Economic Uncertainty index. **National Security EPU*Defense** is the National Security EPU index from Table I multiplied by 1 for firms in defense industries (SICs 348, 372, 376, 379, 381, 871) and 0 otherwise, and analogously for **Healthcare EPU*Health** (SICs 800 to 809) and **Financial Regulation EPU*Finance** (SICs 600 to 699). All regressions weighted by the firm's average sales in the sample period. Standard errors based on clustering at the firm level.

Table III
Robustness Checks for Option-Implied Stock Price Volatility and Policy Uncertainty

Specification	(1) Realized Volatility	(2) 182-day Implied Volatility	(3) Add Purchase Forecast	(4) Add 12 qtrs Future Purchases	(5) Firm-level Intensity	(6) Belo et al. (2013) Intensity	(7) Beta Intensity	(8) 10-K Risk Measure	(9) $500m+ Sales Firms
Log(EPU)×Intensity	0.346***	0.178***	0.175***	0.258***	0.192***	0.456***	0.283**	0.378*	0.237***
	(0.089)	(0.073)	(0.070)	(0.086)	(0.045)	(0.101)	(0.118)	(0.217)	(0.071)
(Federal Purchases/ GDP)×Intensity	-23.72	-27.47***	-58.28***	-7.05	-14.20	-13.60	6.157	27.16	-31.03
	(14.71)	(11.77)	(15.35)	(16.74)	(10.03)	(27.64)	(14.97)	(64.17)	(12.40)
(Forecasted Federal Purchases/GDP)×Intensity			32.61***						
			(6.27)						
Firm and Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,578	136,578	136,578	73,703	132,628	134,381	133,304	112,023	42,771
Number of Firms	5,460	5,460	5,460	3,070	5,219	5,374	5,328	3,717	1,056

Notes: The sample period is 1996 to 2012. The dependent variable is the 30-day implied volatility for the firm, averaged over all days in the quarter, except that column (1) uses the realized daily volatility over the quarter, and column (2) uses the average 182-day implied volatility. See the notes to Table II for additional variable definitions. Standard errors based on clustering at the firm level.

Table IV
Policy Uncertainty and Firm Level Investment, Employment and Sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	I/K	I/K	I/K	I/K	ΔEmp	ΔEmp	ΔEmp	ΔEmp	ΔRev
Δ Log(EPU)×Intensity	-0.032***	-0.032***	-0.024**	-0.029***	-0.213**	-0.227**	-0.220**	-0.220**	-0.128
	(0.010)	(0.010)	(0.011)	(0.010)	(0.084)	(0.089)	(0.118)	(0.094)	(0.096)
Δ(Federal Purchases/ GDP)×Intensity	8.20***	8.04***	12.12***	8.85***	10.79	15.60***	3.19	10.99	20.39**
	(2.86)	(2.86)	(3.18)	(2.87)	(7.41)	(8.04)	(12.56)	(7.88)	(9.43)
Δ(Forecasted Federal Purchases/GDP)×Intensity		1.01				-4.65***			
		(0.828)				(2.89)			
Δ Log(Defense EPU) × Defense Firm				0.002				0.018	
				(0.004)				(0.017)	
Δ Log(Healthcare EPU) × Health Firm				-0.012***				-0.005	
				(0.002)				(0.025)	
Δ Log(Fin. Reg. EPU) × Finance Firm				-0.002***				0.003	
				(0.001)				(0.005)	
Periodicity	Quarterly	Quarterly	Quarterly	Quarterly	Yearly	Yearly	Yearly	Yearly	Yearly
3 Yrs Fed purchase leads	No	No	Yes	No	No	No	Yes	No	No
Observations	708,398	708,398	411,205	708,398	162,006	162,006	107,205	162,006	151,473
Number of Firms	21,636	21,636	13,563	21,636	17,151	17,151	11,505	17,151	15,749

Notes: The sample period runs from 1985 to 2012. All columns include a full set of firm and time effects. **I/K** is the investment rate defined as $CapEx_t$/(Net Plant, Property and Equipment)$_{t-1}$. **ΔEmp** is the employment growth rate measured as (emp_t - emp_{t-1})/ (0.5×emp_t + 0.5×emp_{t-1}), and **ΔRev** is the corresponding revenue growth rate. Δ(**Federal Purchases/GDP)×Intensity** is the change in (Federal Purchases/GDP) from NIPA tables in the next quarter in quarterly specifications and in the next year in annual specifications, multiplied by the firm-level policy exposure intensity variable. Δ(**Forecasted Federal Purchases/GDP)×Intensity** instead uses the mean forecasted change in (Federal Purchases/GDP) from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters, drawing on NIPA data for the current values and forecast data for the future values. See the notes to Table II for additional variable definitions. Standard errors based on clustering at the firm level.