THE
QUARTERLY JOURNAL
OF ECONOMICS

Vol. 131 November 2016 Issue 4

MEASURING ECONOMIC POLICY UNCERTAINTY*

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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 U.S. 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, health care, 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 vector autoregressive setting, for 12 major economies. Extending our U.S. index back to 1900, EPU rose dramatically in the 1930s (from late 1931) and has drifted upward since the 1960s. *JEL Codes:* D80, E22, E66, G18, 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.

The Quarterly Journal of Economics (2016), 1593–1636. doi:10.1093/qje/qjw024.
Advance Access publication on July 11, 2016.

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 International Monetary Fund (IMF) (2012, 2013) suggest that uncertainty about U.S. and European fiscal, regulatory, and monetary policies contributed to a steep economic decline in 2008–2009 and slow recoveries afterward.[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 U.S. newspapers that contain the following trio of terms: “economic” or “economy”; “uncertain” or “uncertainty”; and one or more of “Congress,” “deficit,” “Federal Reserve,” “legislation,” “regulation,” or “White House.” 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 U.S. newspapers published throughout the past century. 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 Herbert Hoover, and then President Franklin 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 indexes for 11 other countries, including all G10 economies. These indexes are particularly helpful in countries with fewer alternative uncertainty measures. We develop category-specific

1. “Widespread 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” (Federal Open Market Committee 2009) See also IMF (2012, pp. xv–xvi and 49–53, and 2013, pp. 70–76).

2. Our data are available at monthly and daily frequencies at http://www.policyuncertainty.com and are carried by Bloomberg, Haver, FRED, and Reuters.

policy uncertainty indexes for the United States by specifying more restrictive criteria for those articles that contain terms about the economy, policy, and uncertainty. For example, we develop indexes of health care policy uncertainty and national security policy uncertainty based on the presence of additional terms like "health care," "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 about 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 EPU and other measures of economic uncertainty, for example, implied stock market volatility. Second, we also show a strong relationship between our index and other measures of policy uncertainty, for example, the frequency with which the Federal Reserve System's Beige Books mention policy uncertainty. Third, we find very similar movements in EPU indexes 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 U.S. newspapers. Working under close supervision, teams of University of Chicago students underwent a training process and then carefully read overlapping sets of randomly selected 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 indexes (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 indexes is uncorrelated with GDP growth rates and with the level of EPU.

Finally, our indexes have a market use validation: commercial data providers that include Bloomberg, FRED, Haver, and Reuters carry our indexes to meet demands from banks, hedge funds, corporations, and policy makers. This pattern of market adoption suggests that our indexes 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 health care 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, health care, 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 health care 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 U.S. data and to an international panel VAR that exploits our EPU indexes for 12 countries. The U.S. VAR results indicate that a policy uncertainty innovation equivalent to the actual EPU increase from 2005–2006 to 2011–2012 foreshadows declines of about 6% in gross investment, 1.1% in industrial production, and 0.35% in employment. The 12-country panel VAR yields similar results.[3] Although our results are not necessarily causal, one plausible interpretation of our micro and macro evidence is that

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.

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 article relates to at least three strands of literature. 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 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., Pastor and Veronesi 2013; Gilchrist, Sim, and Zakrajsek 2014), managerial risk aversion (e.g., Panousi and Papanikolaou 2012), and interactions between nominal rigidities and search frictions (Basu and Bundick 2012; 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]

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), Bachman, Elstener, and Sims (2013), Bloom et al. (2014), and Scotti (2016), 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, Philipson, and Uhlig (2016) develop evidence that government-induced uncertainty about profitability generates a large equity risk premium for firms in the health care 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.

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

II. Measuring EPU

We build indexes 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 "noneconomic" policy matters, for example, 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 indexes for the United States from 1985 onward and then turn to indexes for specific policy categories, indexes for other countries, and historical indexes for the United States and United Kingdom.

6. Earlier drafts of this article include index components based on (i) the present value of future scheduled tax code expirations and (ii) 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 http://www.policyuncertainty.com.

II.A. U.S. Economic Policy Uncertainty Indexes from 1985

Our modern monthly EPU index for the United States 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 trio of terms: "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 standard deviation from 1985 to 2009 and then average across the 10 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: (i) Compute the times-series variance, σ_i^2, in the interval T_1 for each paper i. (ii) 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. (iii) Compute the mean over newspapers of Y_{it} in each month to obtain the series Z_t. (iv) Compute M, the mean value of Z_t in the interval T_2. (v) 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 indexes.

Figure I plots the resulting index, which shows clear spikes around the Gulf Wars, close presidential elections, the 9/11 terrorist attack, the stimulus debate in early 2008, the Lehman Brothers bankruptcy and TARP legislation in late 2008, the summer 2011 debt ceiling dispute, and the battle over the "fiscal

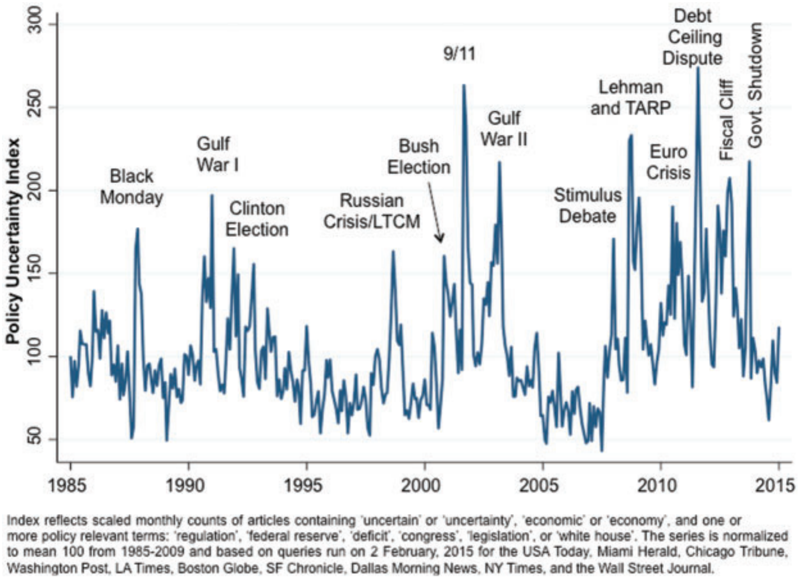


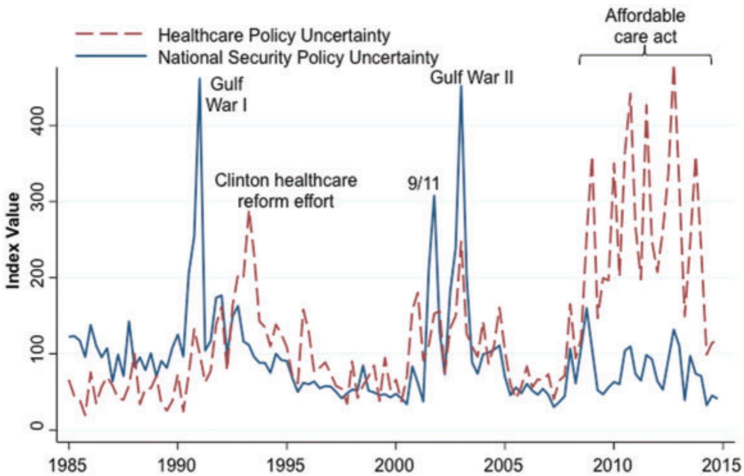
FIGURE I

EPU Index for the United States

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 quite a lot of press coverage.[7]

In addition to our monthly index, we produce a daily EPU index using the Newsbank news aggregator, which covers around 1,500 U.S. 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 leave the Newsbank archive, and its count of newspapers expands greatly over time, compositional shifts potentially distort the longer term behavior of the daily EPU

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 EPU by our measure.



Indices reflect scaled monthly counts of articles containing the same triple as in Figure 1 ***and*** one or more terms pertaining to national security (e.g., "war", "terrorism", or "department of defense") and healthcare (e.g., "healthcare", "hospital", or "health insurance"), respectively, for the National Security and Healthcare indices. Each series is normalized to mean 100 from 1985-2009 and based on queries run Jan 18, 2015 on Access World News Newsbank newspaper archive, which covers about 1,500 US papers.

FIGURE II

National Security and Health Care EPU Indexes

index. Hence, we focus on our 10-paper monthly EPU index, but the daily index provides a useful high-frequency alternative.[8]

II.B. EPU Indexes for Policy Categories

To create indexes for policy categories, we apply additional criteria to those articles that contain our trio 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 11 policy categories and subcategories. We use Newsbank for the category indexes, because its high text density facilitates measurement by time period and policy category. As seen in Figure II, 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 health care EPU index

8. We update the daily EPU index at approximately 9 a.m. EST each day and post it at http://www.policyuncertainty.com.

rose sharply during the Clinton health care reform initiative in 1993–1994 and has fluctuated at high levels from 2009 to 2014.

Table I reports all 11 category-specific EPU indexes.[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 11 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% of the 1985–2014 average EPU frequency and 43% $\left(\frac{54.8}{128.5}\right)$ 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 precrisis years to 61.5 in 2008:9 to 2009:12 and 78.3 from 2010 to 2013. Health care 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 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

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.

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.

TABLE I

ECONOMIC POLICY UNCERTAINTY BY POLICY CATEGORY AND TIME PERIOD, 1985–2014

Time period	1985:1–1990:6 Mid-80s to Gulf War I	1990:7–1991:12 Gulf War I	1992:1–2001:8 1990s boom to 9/11	2001:9–2002:12 9/11 attacks	2003:1–2007:6 2000s boom	2007:7–2008:8 Early credit crunch	2008:9–2009:12 Lehman collapse & recession	2010:1–2013:10 Fiscal policy battles	1985:1–2014:12 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
Health care	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 February 12, 2015, on U.S. 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 health care and entitlement programs. Second, a newspaper article that meets the "economy," "policy," and "uncertainty" criteria can refer to more than one policy category.

departures—for example, war and national security threats produce declines in partisan conflict but increases in policy uncertainty. Shoag and Veuger (2015) develop policy uncertainty indexes for U.S. 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 U.S. 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 Indexes for Other Countries

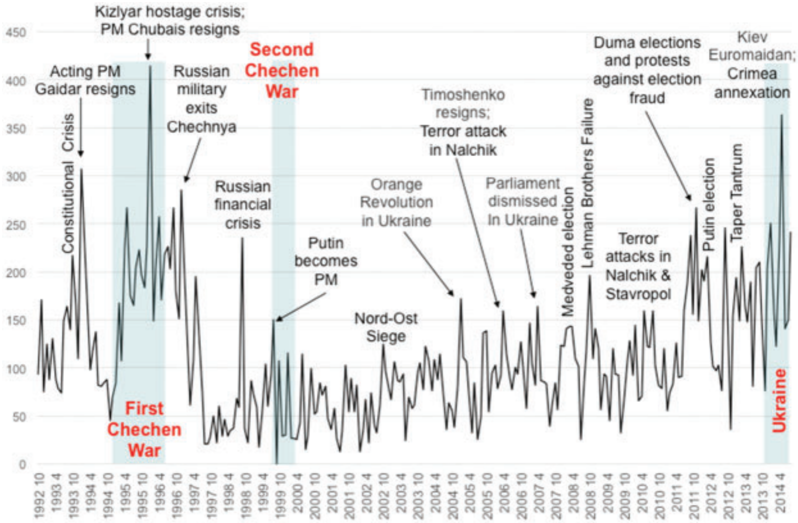
We also construct EPU indexes for 11 other major economies.[11] As with our U.S. index, we first obtain a monthly count of articles that contain a trio of terms about the economy (E), policy (P), and uncertainty (U). We then scale the raw counts, standardize each newspaper's variation, average across 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 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 III displays the EPU index for Russia, and Online Appendix Figures A1–A10 display the other country-level

11. We have recently developed additional EPU indexes for Australia and Brazil and assisted other researchers in developing EPU indexes for Holland and Ireland. We are open to proposals to developing indexes for other countries.

12. For certain papers outside the United States, 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."

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.



Index reflects scaled monthly counts of articles in Kommersant with Russian terms for 'uncertain' or 'uncertainty', 'economic' or 'economy', and one or more selected policy terms. The series is normalized to 100 and runs from October 1992 to August 2014.

FIGURE III

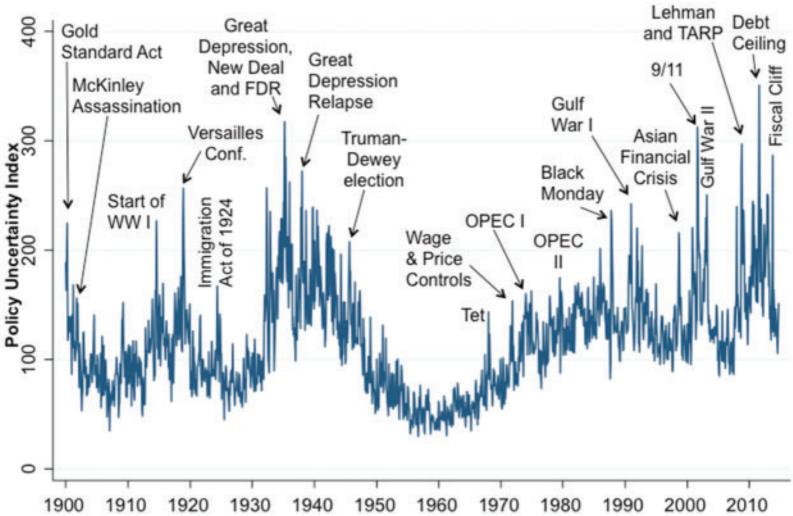
Index of EPU for Russia

indexes.[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 U.S. 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 indexes across 12 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 Indexes for the United States and United Kingdom*

We also construct long-span monthly EPU indexes 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*

14. We provide regular monthly updates of the country-level EPU indexes at http://www.policyuncertainty.com.



Index reflects scaled monthly counts of articles in 6 major newspapers (Washington Post, Boston Globe, LA Times, NY Times, Wall Street Journal, and Chicago Tribune) that contain the same triple as in Figure I, except the economy term set includes "business", "commerce" and "industry" and the policy term set includes "tariffs" and "war". Data normalized to 100 from 1900-2011.

FIGURE IV

U.S. Historical Index of EPU

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 indexes 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 twentieth century. Based on results of the audit analysis described later, we also expanded the P term set for the historical indexes to include “tariff” and “war.”

Figure IV and Online Appendix Figure A1 display the historical EPU indexes for the United States and United Kingdom. Indexes for these two countries exhibit similarities and notable differences. For example, the elevation of EPU levels in the 1930s is dramatic in the United States but modest in the United Kingdom, which experienced a less severe output fall during the Great Depression. World Wars I and II are more prominent in the United Kingdom 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 United Kingdom (which suffered severe economic turmoil over this period, including the IMF bailout and resignation of Prime Minister Harold Wilson) but not in the United States. The post-1960s upward drift of EPU evident for the United States is absent for the United Kingdom. This long-term U.S.-U.K. 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 Section I, using newspaper-based measures of EPU 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 indexes, and collect other information about the nature of policy uncertainty. Next we consider the role of political slant in our EPU index. Last, 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 U.S. EPU indexes 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.

1. Audit Process. We began by reading a few hundred newspaper articles, typically in batches of 50, and comparing notes to

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.

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 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 refine our audit guide. The resulting 65-page guide serves as 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

16. Only 0.5% 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 http://www.policyuncertainty.com/Audit_Guide.pptx.

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.

2. 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 EPU. Using these records, we identified 15 terms that appear often in newspaper discussions of EPU from 1985 to 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—that is, 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."

Online Appendix Figures B1 to B6 display alternative EPU indexes 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, for example, 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]

18. We reviewed more than 15,000 articles across the preaudit 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.

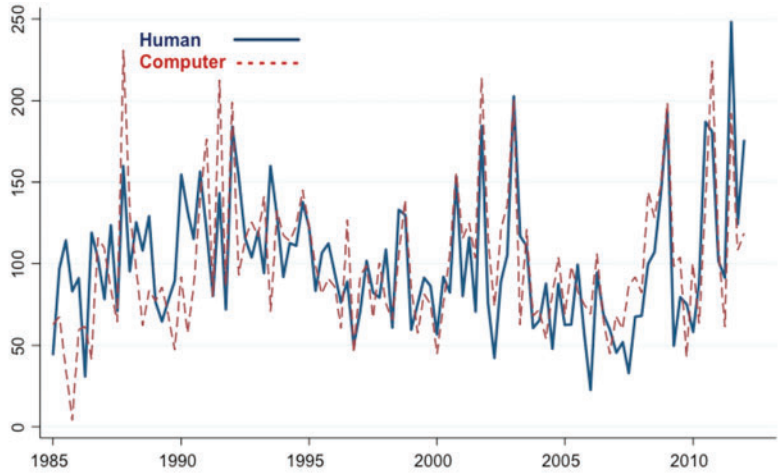
19. Our consideration of compound text filters focused on terms that materially lowered the false negative rate when added to the baseline term set—at the cost of

We repeated this process to obtain the P term set for the historical EPU index in Figure IV, 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 twentieth century and with U.S. participation in World Wars I and II, the Korean War, and the Vietnam War, all of which involved much greater per capita rates of U.S. military deployments and casualties than more recent military conflicts.

3. 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 indexes. 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 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 indexes. There are differences between the two series—for example, 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 Online Appendix Figure C1, we find a correlation of 0.93 between the human and computer EPU indexes.

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 humans. 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

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*, February 14, 1991. The article discusses economic uncertainty and includes remarks about taxable and tax-exempt securities, but it contains no discussion of policy matters.



Index comparison from 1985 Q1 to 2012 Q1 based on 3,723 articles (4,388 audits) in the Chicago Tribune, Dallas Morning News, LA Times, Miami Herald, NY Times, San Francisco Chronicle, Washington Post and Wall Street Journal. Series are plotted quarterly to reduce sampling variability, with an average of 33 articles per quarter. Each series is normalized to 100 from 1985-2009. See text for additional discussion of the audit process and this comparison.

FIGURE V

Human and Computer EPU Indexes

performance of our automated classification criteria. However, it's 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 later, to assess the reliability of newspaper content for the purposes of constructing an EPU index.

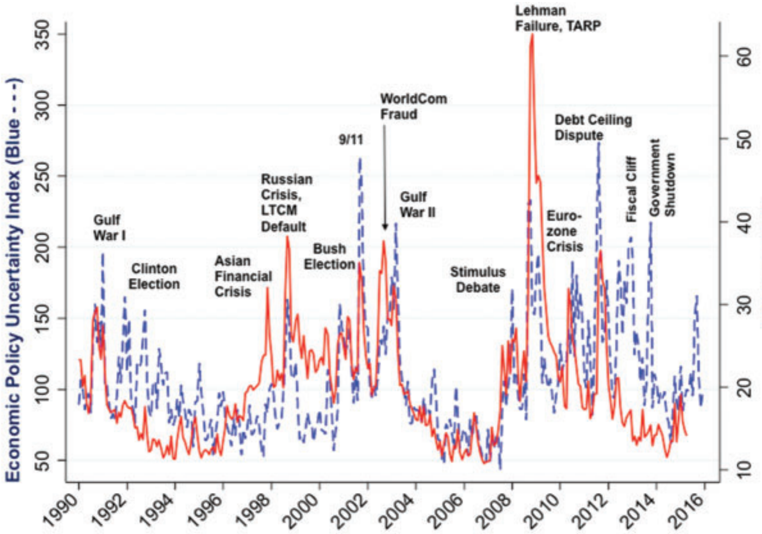
For downstream econometric applications, we also care about the time-series properties of the net error rate, given by the difference between the computer and human EPU index values. Calculating this net error rate from the series in Figure V, we find that it is essentially uncorrelated with quarterly 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).

4. Other Audit Results. Our audit study also speaks to several other questions related to our EPU index. First, only 5% 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% of $\text{EPU}^{\text{H}} = 1$ articles discuss uncertainty about who will make future economic policy decisions, 68% discuss uncertainty about what economic policies will be undertaken (or when), and 47% discuss uncertainty about the economic effects of past, present, or future policy actions. Third, the share of $\text{EPU}^{\text{H}} = 1$ articles that discuss who will make future economic policy decisions triples in presidential election years, compared with other years, indicating that the nature of policy uncertainty shifts substantially over the election cycle.[20] Fourth, 32% of $\text{EPU}^{\text{H}} = 1$ 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. Online Appendix Figure C3 plots the "left" and "right" versions of our EPU index. They move together closely,

20. We also find electoral cycle effects on the level of policy uncertainty in a multicountry setting. In particular, we merge our country-level EPU indexes with data on the timing and closeness of democratic national elections from Julio and Yook (2012, 2016), 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 $\ln(1 + |\text{percentage voting gap between first- and second-place finishers}|)$ 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.



The figure shows the U.S. EPU Index from Figure I and the monthly average of daily values for the 30-day VIX.

FIGURE VI

U.S. EPU Compared to 30-Day VIX

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 with 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 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 strong financial and stock market connections. 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.

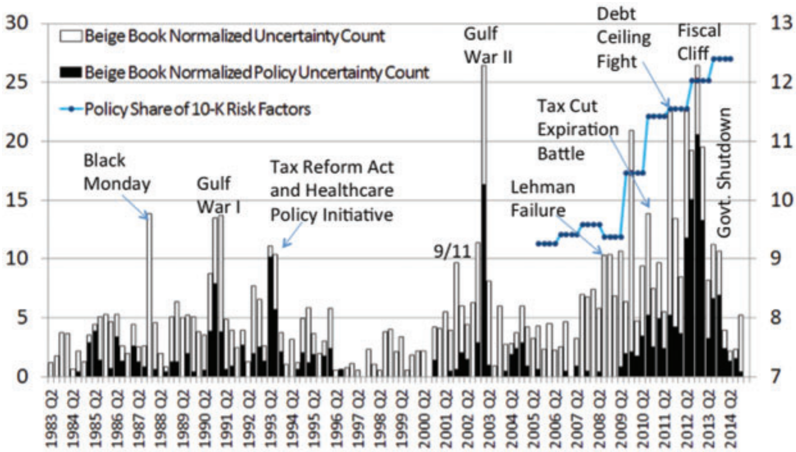
Of course, the two measures differ conceptually in several respects. While the VIX reflects implied volatility over a 30-day look-ahead period, our EPU index involves no explicit horizon. The VIX pertains to uncertainty about equity returns, while the EPU index reflects policy uncertainty, and not just 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 Online 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.

1. 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 12 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.

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, Online Appendix 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.



The left scale shows frequency counts per Beige Book (normalized by word count) of "uncertainty" and references to policy uncertainty. The right scale reports the percentage of sentences in Part 1A (Risk Factors) of annual 10-K filings that contain one or more of the policy terms listed in Online Appendix E. The correlation between the Beige Book Normalized Policy Uncertainty Count and the EPU index is 0.54.

FIGURE VII

Policy Uncertainty Measures Based on Textual Analysis of the Fed's Beige Books and Part 1A (Risk Factors) of Firms' 10-K Filings

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 BBs also point to fiscal policy as the most important source by far of elevated policy uncertainty in recent years. Financial regulation and sovereign debt concerns figure more prominently in the BBs than in newspapers. In contrast to newspapers (but rather unsurprisingly) the BBs 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] Although 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]

2. 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 Online 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 IV 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 indexes contain useful information about the extent and nature of economic policy uncertainty. Compared to other policy uncertainty measures, newspaper-based indexes offer distinct advantages. They can be extended to many countries and backward in time, sometimes by a century or more. For large countries like the United States, it is feasible to construct useful newspaper-based

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. Online 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% for fiscal year 2005 to 17.0% for 2013, and the median falls from 15.2% to 8.7%. In other words, the average firm perceives policy risks as increasingly important from 2005 to 2013 relative to other risks.

indexes at a daily frequency and by region. Newspaper-based indexes are readily disaggregated and parsed to develop category-specific indexes.

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 U.S. 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 U.S. health care 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 U.S. subsidiaries.[25] This match yields the parent firm's revenue derived from federal contracts, which we allocate to three-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 three-digit industry by year. To smooth out high-frequency variation from lumpy contract awards, we

25. We do so using Dunn & Bradstreet's U.S. 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").

average these ratios from 2000 to 2013 to obtain our exposure measure for each three-digit SIC. At the top end, firms operating in the guided missiles and space vehicles and parts industry (SIC 376) derive 78% of their revenues 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 three-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

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)	
$\frac{\text{Federal purchases}}{\text{GDP}}$	−19.30***		−7.75***		−17.40***		
	(1.50)		(1.49)		(1.49)		
$\frac{\text{Federal purchases}}{\text{GDP}}$ × 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)
Health care 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. $\frac{\text{Federal purchases}}{\text{GDP}}$ 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 health care EPU × health (SICs 800 to 809) and financial regulation EPU × finance (SICs 600–699). All regressions weighted by the firm's average sales in the sample period. Standard errors based on clustering at the firm level. ***p <0.01, **p<0.05, *p<0.1

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 covaries 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 U.S. 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

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.

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, health care, engineering services, and heavy construction.

Columns (5) and (6) run a similar evaluation for the 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 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 health care sectors. These category-specific measures potentially capture a broad range of impact channels, including ones that involve regulatory policy. Reassuringly, all three measures yield positive, statistically significant coefficients at the 1–10% 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 II). Similarly, implied volatility for firms in the health care sector responds to the health care EPU index, which rose during the Clinton health care 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 minuscule 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). Online 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 health care firms, mainly due to the run-up in their respective category-specific EPU indexes, 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 the finance sector, 7.5 log points in health care, 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, Gala, and Li (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

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)
$(\frac{\text{federal purchases}}{\text{GDP}})$ × 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)
$(\frac{\text{Forecasted federal purchases}}{\text{GDP}})$ × 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 1996–2012. 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. ***p<0.01, **p<0.05, *p<0.1

coefficient in a regression of the firm's daily stock returns on our daily EPU index from 1985 to 1995, which predates 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 onward only, whereas the regression sample starts in 1996. Column (9) 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, Online 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

27. The sample shrinks for several reasons. First, the Securities and Exchange Commission 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, e.g., Campbell et al. (2014). See Online Appendix E for additional discussion.

TABLE IV

POLICY UNCERTAINTY AND FIRM-LEVEL INVESTMENT, EMPLOYMENT, AND SALES

Dependent variable	(1) I/K	(2) I/K	(3) I/K	(4) I/K	(5) ΔEmp	(6) ΔEmp	(7) ΔEmp	(8) ΔEmp	(9) 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)
$\Delta\frac{\text{Federal purchases}}{\text{GDP}}$ × 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)
$\Delta\frac{\text{Forecasted Federal purchases}}{\text{GDP}}$ × 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(health care 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 $\frac{\text{CapEx}_t}{(\text{NetPlant,Property and Equipment})_{t-1}}$. ΔEmp is the employment growth rate measured as $\frac{\text{emp}_t-\text{emp}_{t-1}}{0.5\times\text{emp}_t+0.5\times\text{emp}_{t-1}}$, and ΔRev is the corresponding revenue growth rate. $\Delta\frac{\text{Federal purchases}}{\text{GDP}}$ × intensity is the change in $\frac{\text{federal purchases}}{\text{GDP}}$ 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. $\Delta\frac{\text{Forecasted federal purchases}}{\text{GDP}}$ × intensity instead uses the mean forecasted change in $(\frac{\text{federal purchases}}{\text{GDP}})$ 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. ***p <0.01, **p<0.05, *p<0.1

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 $\Delta(\log(\text{EPU}))$ $*$ Intensity and $\Delta(\frac{\text{federal purchases}}{\text{GDP}}) *$ 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, for example, 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 $\Delta\log(\text{EPU})*$ Intensity in column (1) imply a one-time investment rate drop of 0.68 percentage point ($= 0.856 * 0.032 * 0.25 * 100$), which is about one sixth of the median firm-level investment rate of 4.2%. Although this calculation rests on a large EPU swing, there were several other large EPU moves during the sample period—for example, an 82-point fall 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 purchases, the estimates imply that swings in policy uncertainty involve material changes in investment rates.

In column (2) we control for $\Delta(\frac{\text{Forecasted Federal Purchases}}{\text{GDP}})$ $*$ 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 $\Delta(\log(\text{EPU}))*$ Intensity, again

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).

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

very similar to column (1).[29] In column (3) we include the average $\Delta(\frac{\text{Forecasted Federal Purchases}}{\text{GDP}}) * \text{Intensity}$ 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 health care 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 changes (Compustat lacks quarterly employment data). As with investment rates, we find sizable and statistically significant negative coefficients on policy uncertainty changes 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% 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 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

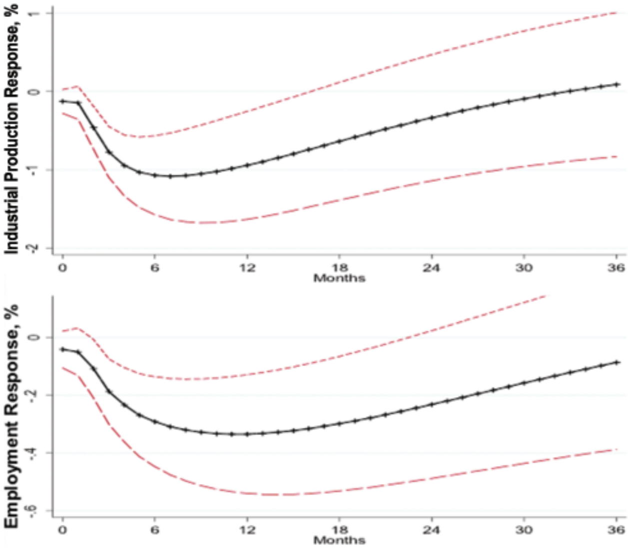
inventories and deferred tax credits, and the denominator is the book value of plant, property, and equipment.

employment growth. To do so, we return to Online Appendix 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% drop for firms in the health care 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 U.S. 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&P500 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 2005–2006 (before the financial crisis and recession) to its average value in 2011–2012 (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 U.S. 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 Online



VAR-estimated impulse response functions for industrial production and employment to an EPU innovation equal to the increase in the EPU index from its 2005-2006 to its 2011-2012 average value, with 90 percent confidence bands. Identification based on three lags and a Cholesky decomposition with the following ordering: EPU index, log(S&P 500 index), federal reserve funds rate, log employment, log industrial production. Fit to monthly data from 1985 to 2014.

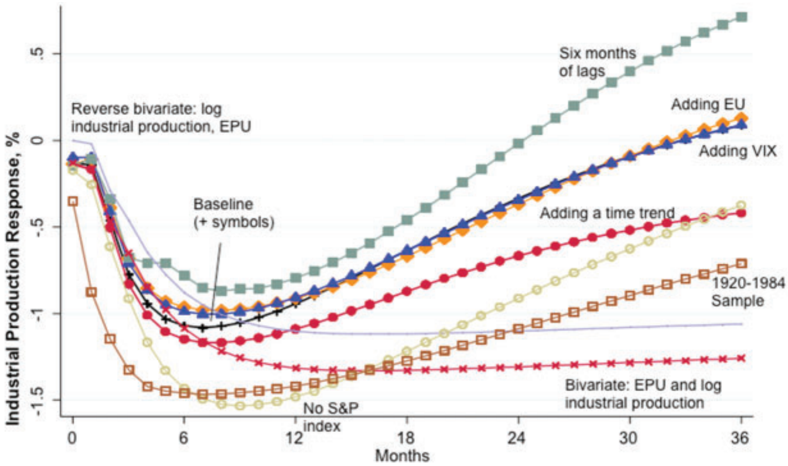
Figure VIII

Industrial Production and Employment Responses to EPU Shock, VAR Fit to Monthly U.S. Data

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



The baseline case involves the same sample period, VAR specification and identification as in Figure VIII. The other cases depart from the baseline as indicated. We place EU and VIX after EPU in the ordering. For the "1920-1984" response function, we use monthly data from 1920 to 1984 on log industrial production and EPU in a bivariate VAR with EPU ordered first.

FIGURE IX

U.S. Industrial Production Response to an EPU Shock, Alternative Samples, Specifications, and Identification Assumptions

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

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 five 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.

(Online 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 murky, and the two concepts are tightly linked at a deep level in some theoretical models, for example, Ilut and Schneider (2014). In any event, the EPU index has several important advantages relative to consumer confidence indexes: EPU indexes 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 indexes.

Figure X shows impulse response functions for a panel VAR fit to monthly data from 1985 to 2014 on the 12 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 12-country panel VAR yields results that are similar to the U.S. 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% and a rise in the unemployment rate of about 25 basis points. Online 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 indexes in multicountry time-series analyses also find that policy uncertainty shocks foreshadow deteriorations in macroeconomic outcomes—examples include the International Monetary Fund (2012), Colombo (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

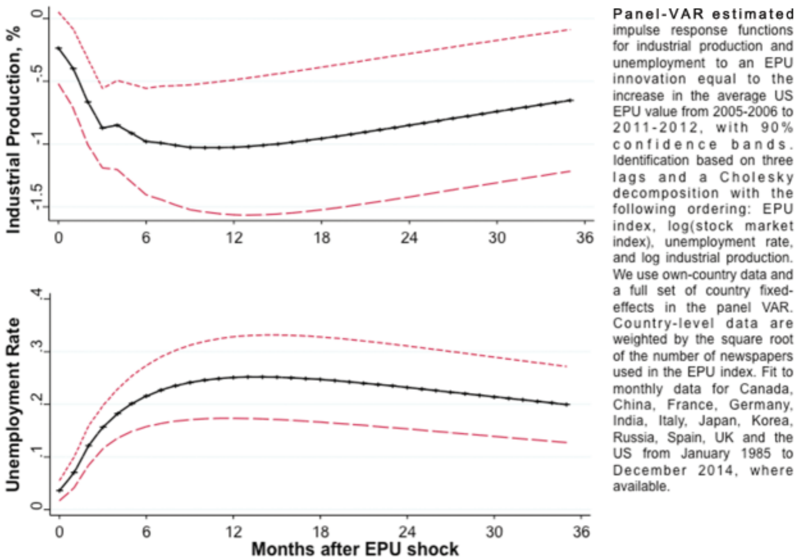


FIGURE X

Responses to an EPU Shock in a Twelve-Country Panel VAR

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&P500), 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

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.

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 U.K. 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 11 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 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.

Supplementary Material

An Online Appendix for this article can be found at QJE online (qje.oxfordjournals.org).

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