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MEASURING ECONOMIC POLICY UNCERTAINTY

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### **ABSTRACT**

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

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# 1. INTRODUCTION

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

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.<sup>2</sup> Our index reflects the frequency of articles in 10 leading US newspapers that contain the following triple: “economic” or “economy”; “uncertain” or “uncertainty”; and one or more of “congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation” or “White House”. As seen in Figure 1, the index spikes near tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the 2011 debt-ceiling dispute and other major battles over fiscal policy. We extend our newspaper-based approach to measuring policy uncertainty along three dimensions: back in time, across countries, and to specific policy categories.

To push back to 1900, we rely on archives for six major US newspapers published throughout the last century. As shown in Figure 2, this long-span EPU index highlights pre-World War II political developments and shocks like the Gold Standard Act of 1900, the outbreak of World War I, the Versailles conference in 1919, and a sustained surge in policy uncertainty from late 1931 when President Hoover, and then President Roosevelt, introduced a rash of major new policies. The index also shows an upward drift since the 1960s, perhaps due to rising political polarization or the growing economic role for government (Baker et al., 2014).

Using similar methods, we construct EPU indices for eleven other countries, including all G10 economies. These indices are particularly helpful in countries with fewer alternative uncertainty measures. We also develop category-specific policy uncertainty indices for the US by specifying more restrictive criteria for those articles that contain our triple of terms about the economy, policy, and uncertainty. As examples, Figure 3 plots indices of healthcare policy uncertainty and national security policy uncertainty based on the presence of additional terms

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

<sup>2</sup> Our data are available at monthly and daily frequencies on [www.policyuncertainty.com](http://www.policyuncertainty.com) and are carried by Bloomberg, Haver, FRED and Reuters.

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

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

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

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

In Section 4 we assess the effects of EPU on the economy in two ways. First, we exploit firm-level differences in exposure to a particular aspect of policy – government purchases of goods and services – to estimate the effects of policy uncertainty working through one channel. To do so, we use micro data from the Federal Registry of Contracts and data on government healthcare spending to calculate the share of firm and industry revenues derived from sales to the government. Next, in firm-level regressions that include time and firm fixed effects and other controls, we find that firms with greater exposure to government purchases respond to policy

uncertainty with heightened stock price volatility and reduced investment and employment. Adding the VIX as an explanatory variable (interacted with firm-level exposure to government purchases), we still find strong effects of policy uncertainty on stock volatility, investment and employment, which points to a policy uncertainty channel at work rather than a broader uncertainty effect. We also find that firms in the defense, healthcare and financial sectors are especially responsive to their own category-specific EPU measures, confirming the information value of these measures and providing additional evidence of policy uncertainty effects.

These firm-level results point to a causal impact of policy uncertainty on investment and employment in sectors that rely heavily on government spending. But they offer limited guidance about the magnitude of aggregate effects, in part because they capture only one specific policy uncertainty channel (government purchases of goods and services).

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

This paper relates to at least three literatures. The first is research on the impact of uncertainty on growth and investment. Theoretical work on this topic dates at least to Bernanke (1983), who points out that high uncertainty gives firms an incentive to delay investment and hiring when investment projects are costly to undo or workers are costly to hire and fire.<sup>4</sup> Of course, once uncertainty recedes, firms increase hiring and investment to meet pent-up demand. Other reasons for a depressive effect of uncertainty include precautionary spending cutbacks by households, upward pressure on the cost of finance (e.g., Gilchrist et al., 2014, and Pastor and Veronesi, 2013), managerial risk-aversion (e.g., Panousi and Papanikolaou, 2012), and

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<sup>3</sup> 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.

<sup>4</sup> Dixit and Pindyck (1994) offer a detailed review of the early theoretical literature. Recent empirical papers include Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta and Terry (2014), Bachman et al. (2013) and Scotti (2014).

interactions between nominal rigidities and search frictions (Basu and Bundick, 2014 and Leduc and Liu, 2015).

Second, there is a literature focused explicitly on policy uncertainty. Friedman (1968), Rodrik (1991), Higgs (1997) and Hassett and Metcalf (1999), among others, consider the detrimental economic effects of monetary, fiscal, and regulatory policy uncertainty. More recently, Born and Pfeifer (2014) and Fernandez-Villaverde et 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.<sup>5</sup>

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 2 describes the data we use to construct our policy uncertainty indices. Section 3 evaluates our EPU measures in several ways and develops additional evidence about movements in policy-related uncertainty over time. Section 4 estimates the firm-level effects of policy uncertainty and the dynamic responses of aggregate outcomes to policy uncertainty shocks. Section 5 concludes and offers some thoughts about directions for future research.

## 2. MEASURING ECONOMIC POLICY UNCERTAINTY

We build indices of policy-related economic uncertainty based on newspaper coverage frequency.<sup>6</sup> We aim to capture uncertainty about *who* will make economic policy decisions, *what* economic policy actions will be undertaken and when, and the economic *effects* of policy actions (or inaction) – including uncertainties related to the economic ramifications of “non-economic”

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<sup>5</sup> 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 (2012) find that trade-policy uncertainty delays firm entry, Gulen and Ion (2015) find negative responses of corporate investment to our EPU index, 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.

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

policy matters, e.g., military actions. Our measures capture both near-term concerns (e.g., when will the Fed adjust its policy rate) and longer-term concerns (e.g., how to fund entitlement programs), as reflected in newspaper articles. We first describe the construction of our monthly and daily EPU indices for the US from 1985 onwards and then turn to indices for specific policy categories, indices for other countries, and historical indices for the US and UK.

## **2.1 US economic policy uncertainty indices from 1985**

Our modern monthly EPU index for the US relies on 10 leading newspapers: USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and Wall Street Journal. We search the digital archives of each paper from January 1985 to obtain a monthly count of articles that contain the following triple: ‘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 3.1.

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, which yields a monthly EPU series for each newspaper. We standardize each newspaper-level series to unit standard deviation from 1985 to 2010 and then average across the ten papers by month. Finally, we normalize the 10-paper series to a mean of 100 from 1985 to 2009. Figure 1 plots the resulting index, which shows clear spikes around the Gulf Wars, close presidential elections, 9/11, the 2009 stimulus debate, the Lehman Brothers bankruptcy and TARP legislation in late 2008, the summer 2011 debt-ceiling dispute and the battle over the “Fiscal Cliff” in late 2012, among other events and developments.<sup>7</sup>

In addition to our monthly index, we also produce a daily EPU index using the Newsbank news aggregator, which covers around 1,500 US newspapers. Newsbank’s extensive coverage yields enough articles to generate a meaningful daily count. Taking monthly averages of our

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

daily index, it correlates at 0.85 with our 10-paper monthly index, indicating a high degree of similarity. Because papers enter and exit the Newsbank archive, and its count of newspapers expands greatly over time, compositional shifts potentially distort the longer-term behavior of the daily EPU index. Hence, we focus below on our 10-paper monthly EPU index, but the daily index provides a useful high-frequency alternative.<sup>8</sup>

## 2.2 EPU indices for policy categories

To create indices for policy categories, we apply additional criteria to those articles that contain our triple of terms about the economy, policy and uncertainty. The additional criteria involve the presence of one or more category-relevant terms: “the Fed”, “central bank”, “interest rate”, “inflation” and so on for the monetary policy category, for example. The appendix reports the full set of terms that define our eleven policy categories and sub-categories. We use Newsbank for the category indices, because its high text density facilitates measurement by time period and policy category. As seen in Figure 3, the national security EPU index spiked sharply in connection with the 9/11 attacks, Gulf War I and the onset of Gulf War II. The healthcare EPU index rose sharply during the Clinton healthcare reform initiative in 1993-94 and has fluctuated at high levels from 2009 to 2014.

Table 1 reports all eleven category-specific EPU indices.<sup>9</sup> It also reports an overall Economic Uncertainty (“EU”) index that drops the policy requirement in the EPU index. The first two rows report average EU and EPU values for the indicated periods, expressed relative to the average EPU value from 1985 to 2014. For example, the EU value of 218.2 says the (scaled) frequency of EU articles from 1985:1 to 1990:6 is somewhat more than twice the average frequency of EPU articles from 1985 to 2014. The next eleven rows report relative frequency values for specific policy categories and time periods. For example, the 54.1 value for “National Security” says the frequency of EPU articles during 2001:9 to 2002:12 that mention national security matters is 54 percent of the 1985-2014 average EPU frequency and 42 percent (54.1/128.5) of the EPU frequency from 2001:9 to 2002:12.

Fiscal matters, especially tax policy, stand out in Table 1 as the largest source of policy uncertainty, especially in recent years. The fiscal policy EPU index rose from values near 33 in the pre-crisis years to 61.5 in 2008:9 to 2009:12 and 78.3 from 2010 to 2013. Healthcare policy

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<sup>8</sup> We update the daily EPU index at approximately 9am EST each day and post it at [www.policyuncertainty.com](http://www.policyuncertainty.com).

<sup>9</sup> In contrast to Figure 3, which normalizes each category-specific EPU series to 100, Table 1 expresses each category-specific EPU series as a percentage of the overall EPU frequency from 1985 to 2014.



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.<sup>10</sup>

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

### **2.3 EPU indices for other countries**

We also construct EPU indices for eleven other major economies. As with our US index, we first obtain a monthly count of articles that contain a triple of terms about the economy (E), policy (P) and uncertainty (U). We then scale the raw counts, standardize each newspaper's variation, average across papers in a country by month, and normalize.<sup>11</sup> 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”

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<sup>10</sup> 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.

<sup>11</sup> For certain papers outside the US, search platform limitations preclude us from scaling by the count of all articles. In these cases, we instead scale by the count of articles containing the common and neutral term “today”.

for India). 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.<sup>12</sup>

Figure 4 displays the EPU index for Russia, and Appendix Figures A1-A10 display the other country-level indices.<sup>13</sup> The Russian index responds to Russian military conflicts, major political developments in Ukraine, the Russian Financial Crisis in 1998, the Lehman Brothers failure in 2008, the 2013 “taper tantrum” triggered by a perceived shift in US monetary policy, and other developments. While the Russian index is noisy, reflecting our reliance on a single paper, it shows that our approach yields useful information even for countries with strong restrictions on press freedoms. Looking at EPU indices across twelve countries, we see that a wide variety of global and domestic factors drive movements in our newspaper-based measures of policy uncertainty.

## **2.4 Long-span EPU indices for the US and UK**

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

Figure 2 and Figure A11 in the appendix display the historical EPU indices for the US and UK. Indices for these two countries exhibit both similarities and notable differences. For example, the elevation of EPU levels in the 1930s is dramatic in the US but modest in the UK, which experienced a less severe output fall during the Great Depression. World Wars I and II are more prominent in the UK EPU series. Gulf Wars I and II are associated with sharp EPU spikes

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<sup>12</sup> 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.

<sup>13</sup> We provide regular monthly updates of the country-level EPU indices at [www.policyuncertainty.com](http://www.policyuncertainty.com).

in both countries. The mid 1970s stands out as a period of unusually high EPU in the UK, which suffered severe economic turmoil during the late 1970s and saw the resignation of Prime Minister Harold Wilson, but not in the US. The post-1960s upward drift of EPU evident for the US is absent for the UK. This long-span US-UK comparison reinforces our earlier inference that a broad mix of domestic and international developments influences the extent of policy uncertainty in any given country.

### **3. EVALUATING OUR POLICY UNCERTAINTY MEASURES**

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

#### **3.1 Audit Study Based on Human Readings**

We spent six months developing an audit process designed to evaluate and refine our US EPU indices and another 18 months running a large-scale human audit study. During the latter phase, student teams working under our close supervision read and coded articles drawn from eight newspapers from 1900 to 2012.<sup>14</sup> We now describe the audit process and results.

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

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<sup>14</sup> To construct our EPU index, it suffices to recover counts of articles that contain certain terms. In contrast, we need full-text articles (machine-readable files or images) to carry out the audit study. We could not access full-text articles for the Boston Globe or USA Today, but we did so for the other eight newspapers.

meet our “economy” and “uncertainty” criteria, which concentrates our (expensive) human resources on samples that are highly germane for our purposes.<sup>15</sup>

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 many articles to multiple auditors. We used the pilot study to develop a training process and to refine our audit guide. The resulting 65-page guide serves as both a training tool and reference manual in our full-scale audit. It explains how to assess whether an article meets our criteria for economic uncertainty and economic policy uncertainty and how to code each field in the audit template.<sup>16</sup> The pilot study also led to improvements in the audit process. For example, to ensure that auditor-learning effects are not confounded with differences across papers or over time, the full-scale audit study presents articles to auditors in a randomized order.

To conduct the full-scale audit, we recruited and trained new teams of research assistants. Each new auditor underwent a training process that included a review of the audit guide and template, trial codings of at least 100 articles (not included in the audit sample), a one-on-one meeting to review the trial codings, and additional trial codings and feedback when needed. We met with the audit teams on a weekly basis to address questions, review “hard calls” and coding differences, and maintain esprit de corps. The auditors reviewed 12,009 articles from 1900 to 2012 that we selected using a two-stage approach:<sup>17</sup> First, we specified a target sample size (higher in 1985-2011 and certain key earlier years), and then we randomly sampled a number of articles for each newspaper and month. To monitor audit quality and sharpen incentives for careful work, we randomly assigned about one quarter of the articles to multiple auditors.

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

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<sup>15</sup> Only 0.5 percent of the articles in our 10 leading newspapers satisfy both the “economy” and “uncertainty” criteria. Thus, the vast majority of all articles read by our auditors would be useless for selecting and evaluating our P term set if we were to sample randomly from all newspaper articles.

<sup>16</sup> The guide includes coding instructions, numerous examples, and FAQs. For example, one of the FAQs asks “Are remarks about uncertain tax revenues grounds for EPU=1?” and answers “Yes, if the article attributes uncertainty about tax revenues partly or entirely to uncertainty about policy choices.... No, if the article attributes uncertainty about tax revenues entirely to uncertainty about economic conditions ...” The audit guide is available at [www.policyuncertainty.com/Audit\\_Guide.pptx](http://www.policyuncertainty.com/Audit_Guide.pptx).

<sup>17</sup> We reviewed more than 15,000 articles across the pre-audit phase, pilot audit, auditor training exercises and full-scale audit, but we draw only on the 12,009 articles in the full-scale audit for our analysis here.

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

Appendix Figures B1 to B6 display alternative EPU indices constructed by dropping the six baseline terms, one at a time. Inspecting these figures, it is apparent that the time-series behavior of our EPU index is not particularly sensitive to any single policy term. We also experimented with compound text filters, e.g., adding {government AND tax} to the baseline term set. In this regard, we focused on terms that materially lowered the false negative rate relative to the baseline term set.<sup>18</sup> “Tax” is the leading example in this regard. Somewhat to our surprise, we were unable to develop simple compound text filters that achieved a lower gross error rate than our baseline term set.

We repeated this process to obtain the P term set for the historical EPU index in Figure 2, 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 20<sup>th</sup> century and with US participation in World Wars I and II, the Korean War and the Vietnam War, all of which involved much greater per capita rates of US military deployments and casualties than more recent military conflicts.

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

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<sup>18</sup> At the cost of even greater increases in the false positive error rate, of course – otherwise, the term in question would have been part of the baseline set.

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 5 compares these human and computer EPU indices. There are differences between the two series – e.g., a larger spike for the summer 2011 debt-ceiling dispute in the human EPU index – but they are quite similar, with a correlation of 0.86. Repeating the same type of comparison using annual data from 1900 to 2010 in appendix Figure C1, we find a correlation of 0.93 between the human and computer EPU indices.

Figures 5 and C1 provide some assurance that our computer-automated EPU classifications track the actual time-series variation in the intensity of concerns about EPU, as judged by intelligent human beings. In this regard, it's worth stressing that our term-set selection criterion makes no use of time-series variation. So Figures 5 and C1 offer something of an independent check on the performance of our automated classification criteria. However, it's also important to understand the limitations of these comparisons. They incorporate our computer-automated EU assignments and, more fundamentally, they rely on the content of newspaper articles. We use other methods, as discussed below, to assess the reliability of newspaper content for the purposes of constructing an EPU index.

For downstream econometric applications, we also care about the time-series properties of net error rates in the computer EPU index. Calculating this net error rate from the series in Figure 5, we find that it is essentially uncorrelated with quarterly real GDP growth rates (correlation of -0.02) and with the “true” (i.e., human) EPU rate in the audit sample (correlation of 0.004).

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

### 3.2 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 their Congressional speech. For example, a newspaper that frequently uses “death tax”, “personal accounts” and “war on terror” (terms preferred by Republicans) falls on the right side of their slant index, and a newspaper that frequently uses “estate tax”, “private accounts” and “war in Iraq” (terms preferred by Democrats) falls on the left side. Appendix Figure C3 plots the “left” and “right” versions of our EPU index. They move together closely, with a correlation of 0.92. This finding suggests that political slant does not seriously distort variation over time in newspaper coverage of EPU and is not a major concern for our index.

### 3.3 Comparisons to Other Measures of Uncertainty and Policy Uncertainty

Another way to evaluate our EPU index is by comparison to other measures of uncertainty and policy uncertainty. The most obvious comparator is the VIX, an index of 30-day option-implied volatility in the S&P500 stock index, available since 1990. As seen in Figure 6, the VIX and the EPU index often move together (correlation of 0.58), but they also show distinct variation. For example, the VIX reacts more strongly to the Asian Financial Crisis, the WorldCom Fraud and the Lehman Brothers collapse – events with a strong financial and stock-market connection. In contrast, the EPU index shows stronger responses to war in the Gulf region, the election of a new president, and political battles over taxes and government spending – events that clearly involve major policy concerns but also affect stock market volatility.

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

price”, “equity price” or “stock market”. The resulting index, shown in Appendix Figure C2, correlates with the VIX at 0.73, considerably higher than the EPU-VIX correlation.<sup>19</sup>

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

Other Text Sources: We also consider uncertainty indicators based on the Beige Book releases before each regularly scheduled meeting of the Federal Open Market Committee (FOMC). The Beige Book, published eight times a year, summarizes in roughly 15,000 words the views and concerns expressed by business and other contacts to the twelve regional Federal Reserve Banks. We count the frequency of “uncertain\*” in each Beige Book, normalized to account for variation in word count.<sup>20</sup> We also read each passage that contains “uncertain\*” to judge whether it pertains to policy matters and, if so, we record the policy category.

Figure 7 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 1. 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 1 (not shown), the Beige Books 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 Beige Books than in newspapers. In sharp contrast to newspapers, the Beige Books almost never mention monetary policy uncertainty.

Figure 7 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 Appendix C. We then divide by the total number of sentences in the Risk Factors section and average over firms by

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<sup>19</sup> We make no effort here to develop an optimal term set for the news index of equity market uncertainty, something we are currently pursuing in other work. Instead, Figure C2 reflects our first attempt and can surely be improved.

<sup>20</sup> 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.



year to obtain the series in Figure 7.<sup>21</sup> While the temporal coarseness of the 10-K filings precludes fine-grained comparisons, our analysis reveals a strong upward drift after 2009 in the degree to which firms express concerns about their exposure to policy-related risk factors.

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 Figure C4, 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 2 is 0.78. The 1930s and the period during and after the Great Recession stand out in both series.

### 3.4 Summary

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

## 4. ESTIMATING THE EFFECTS OF POLICY UNCERTAINTY

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 one channel of impact (government purchases of goods and services). The second uses *macro data* in VAR analyses, capturing multiple channels of influence but offering weaker identification of causal effects. Combining the two approaches, we conclude there is evidence that policy uncertainty raises stock price volatility and lowers investment rates and employment growth rates for firms in government-exposed sectors like defense, healthcare and

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<sup>21</sup> 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.

construction, and that these effects are large enough to matter for aggregate investment, employment, and output.

#### **4.1 Firm-level Analysis of Policy Uncertainty Effects**

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

As a first step, we match the federal contracts database to Compustat firms using DUNS numbers and the names of the parent firm and their US subsidiaries.<sup>22</sup> This match yields the parent firm's revenue derived from Federal contracts, which we allocate to 3-digit SIC industries using industry codes and line-of-business data in Compustat. We then aggregate revenues and contract awards to obtain the ratio of federal purchases to revenues in each 3-digit industry by year. To smooth out high-frequency variation from lumpy contract awards, we average these ratios from 2000 to 2013 to obtain our exposure measure for each 3-digit SIC. At the top end, firms operating in the Guided Missiles and Space Vehicles and Parts Industry (SIC 376) derive 78% of their revenues (in SIC 376) from sales to the federal government. The corresponding figure for selected other industries with high exposures to federal purchases is 39% for Ordnance and Accessories (SIC 348), 27% for Search, Detection, Navigation, Guidance & Aeronautical Systems (SIC 381), 21% for Engineering Services (SIC 871), 20% for Aircrafts and Parts (SIC 372), 15% for Ship and Boat Building and Repairing (SIC 373), 11% for Blank Books, Loose Leaf Binders, and Bookbinding (SIC 278), and 9% for Heavy Construction (SIC 160). Direct sales to the federal government are comparatively small in most other industries.

In a second step, we measure each firm's exposure to government purchases as its revenue-weighted mean (across its lines of business) of the industry-level exposure measures

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<sup>22</sup> We do so using Dunn & Bradstreet's US database of all public and private firms, which includes a firm name, DUNS number, industry and ownership information. In this way, we capture federal contracts of the publicly listed parent firm (e.g. "General Electric") *and* contracts with subsidiaries of the parent firm (e.g. "General Electric Capital Services" and "USA Instruments").

calculated in the first step. If the firm operates in a single 3-digit SIC, then its exposure measure equals the corresponding industry exposure measure. We prefer this two-step approach because it may lessen the scope for reverse causality, and because industry-level measures may better proxy for the firm's ex ante exposure to uncertainty about government purchases. As we show in our robustness investigation, results are similar for a variety of other exposure measures.

#### **4.1.1 Implied Stock Price Volatility**

Table 2 displays results for the estimated effects of policy uncertainty on firms' 30-day implied stock price volatility. We obtain this 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 the implied volatility measure over all trading days in the quarter. We run regressions on a sample that runs from 1996 to 2012 and weight by firm sales, giving more weight to the larger firms that also tend to have more actively traded equity options.

Column (1) reports a very basic specification that regresses logged 30-day implied volatility on our EPU index and the ratio of federal government purchases to GDP, a control for the first moment of policy.  $\log(\text{EPU})$  is highly statistically significant, with the coefficient of 0.432 indicating that a 1% EPU increase is associated with a roughly 0.4% increase in firm-level implied volatility. To put this magnitude in perspective, our EPU index rose by 84 log points (131%) from 2005-06 to 2011-2012, which implies an estimated upward shift of 36.3 log points (44%) in average firm-level implied volatility. The negative coefficient on the control variable in Column (1) says that, conditional on  $\log(\text{EPU})$ , 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  $\log(\text{EPU})$  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 if firms with more exposure to government purchases are more responsive to policy uncertainty movements. Intriguingly, we find very strong evidence for such effects. The coefficient of 0.215 on the  $\log(\text{EPU}) \times \text{Intensity}$  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%.<sup>23</sup>

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 3.3, our EPU index and the VIX have a correlation coefficient of 0.58. Adding the VIX in a specification without firm or time effects knocks out the statistical significance of the EPU term, while the coefficient on the VIX is large (at 0.734) and highly significant. This result is unsurprising since the VIX is the 30-day implied volatility on the S&P500 index, and it should be highly correlated with the average 30-day implied volatility for publicly listed US firms.

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

Columns (5) and (6) run a similar evaluation for the Economic Uncertainty (EU) index, yielding similar results. In column (5) we run a regression with the EPU, EU and Federal Purchases/GDP measures, but no time or firm fixed effects. The EU index dominates with a large and highly significant coefficient, knocking out the EPU measure. 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 terms of explaining firm-specific movements in option-implied volatility, and the EPU effects are large.

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<sup>23</sup> Using a quite different empirical design and source of variation, Kelly, Pastor and Veronesi (2015) find evidence that policy uncertainty related to election outcomes also raises option-implied stock market volatility.

Finally, in column (7) we add category-specific EPU measures from Section 2.2 for firms in defense, healthcare and construction. Reassuringly, we see that all three of these measures are positive and statistically significant at the 1 to 10 percent level. This result tells us, for example, that implied volatility for defense firms is most responsive to the National Security EPU index, which jumped up in Gulf Wars I and II and after the 9/11 terrorist attacks, as we saw in Figure 3. Similarly, implied volatility for firms in the healthcare sector is especially responsive to the Healthcare EPU index, which rose during the Clinton healthcare reform initiative and in response to uncertainties surrounding the Affordable Care Act.

Table 3 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 for government purchases relative to GDP<sup>24</sup> (interacted with firm-level exposure) as an additional control, and Column (4) uses actual future government purchases relative to GDP (again interacted) as a control. Column (5) replaces our preferred firm-level exposure measure (calculated by the two-step method described above) with a one-step measure calculated directly from the firm's own sales to the federal government. Column (6) uses the Belo et al. (2013) measure of industry-level exposure to government purchases, which exploits the input-output matrix to capture direct and indirect effects of government purchases. Column (9) restricts attention to firms with at least \$500 million in annual sales. These alternative measures and specifications yield highly statistically significant results similar to Column (2) in Table 2.

Columns (7) and (8) in Table 3 consider two entirely different approaches to measuring firm-level exposure to government policy risks. In column (7), we measure exposure by the slope coefficient in a regression of the firm's daily stock returns on our daily EPU index from 1985 to 1995, which pre-dates the sample period in Tables 2 and 3. 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 that we derived from 10-K filings and plotted over time in Figure 7. Now, however, we use that measure at the firm level, averaging over available years. We again find sizable positive effects of EPU on firm-level volatility, but the coefficient on the log(EPU) interaction term is less statistically significant than

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<sup>24</sup> These forecasts come from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.

in the other columns, and the standard error is large. We lose more than one-quarter of our sample when using this measure,<sup>25</sup> which contributes to the loss in precision. Moreover, the measure used in column (8) reflects the firm’s perceived exposure to policy risk factors from 2006 onwards only, whereas the regression sample starts in 1996.

Finally, Appendix Table A1 returns to the baseline specification in Table 2 Column (2) and replaces the key  $\log(\text{EPU})$  interaction term by  $\log(\text{EPU}/X)$ , where  $X$  corresponds to the newspaper-based E (“Economy”), P (“Policy”), U (“Uncertainty”), EP, EU or PU index. These variants involve different choices about how to scale the EPU frequency counts. As shown in Table A1, all of these variants yield slope coefficients on the key  $\log(\text{EPU}/X) \times \text{Intensity}$  variable that are statistically indistinguishable from the point estimate in Table 2 Column (2), and all are statistically significant except for the specification that uses  $\log(\text{EPU}/\text{EU})$ . As we’ve already seen in Table 2 Column (6), however, when we allow the  $\log(\text{EPU})$  and  $\log(\text{EU})$  terms to enter freely into the interacted specification, the coefficient on the  $\log(\text{EPU}) \times \text{Intensity}$  remains large and statistically significant. Thus, the main finding in Tables 2 and 3 does not rest on how we scale the frequency of newspaper articles about economic policy uncertainty.

#### **4.1.2 Investment Rates and Employment Growth**

Table 4 investigates how policy uncertainty affects firm-level investment rates and employment growth. We now have data from 1985 to 2012 and, as before, weight by firm sales. We use our preferred measure of the firm’s policy exposure intensity and a full set of time and firm effects in all Table 4 specifications. Column (1) displays a regression of the firm-level investment rate on  $\log(\text{EPU}) \times \text{Intensity}$  and  $(\text{Federal Purchases}/\text{GDP}) \times \text{Intensity}$ . The former has a significant negative coefficient of -0.032, and the latter has a significant positive coefficient. These results are in line with standard predictions of investment-under-uncertainty models, e.g., Bernanke (1983), Dixit and Pindyck (1994) and Bloom, Bond and Van Reenen (2007).

The magnitude of the estimated policy uncertainty effect is sizable. To see this point, recall that the EPU index rose 84 log points from 2005-06 to 2011-12. For a firm that sells 25% of its output to the federal government, this EPU increase and the coefficient on

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<sup>25</sup> Several factors are in play. First, the SEC did not mandate a Risk Factors discussion before 2006, so we cannot obtain this measure for firms that delisted before 2006. Second, some publicly listed firms are exempt from the Risk Factors disclosure requirement, and some may not comply. Third, our web-scraping and automated text-reading methods may not capture all relevant 10-K filings, perhaps because some firms present their discussion of Risk Factors in an unusual format. Fourth, it is not always possible to match data from 10-K filings to Compustat. Our match rates compare favorably to similar efforts by other researchers. See Appendix E for additional discussion.

$\log(\text{EPU}) \times \text{Intensity}$  in Column (1) imply an investment rate drop of 0.67 percentage points ( $=0.84 \times 0.032 \times 0.25 \times 100$ ), about one tenth of the average firm-level investment rate of 6.6 percentage points. Hence, for firms with high exposures to government purchases, the estimates imply that elevated policy uncertainty in recent years materially depressed investment.

In column (2) we control for  $(\text{Forecasted Federal Purchases}/\text{GDP}) \times \text{Intensity}$ , given the forward-looking nature of investment decisions, and obtain very similar results on the main coefficient of interest. In column (3) we include the average  $(\text{Federal Purchases}/\text{GDP}) \times \text{Intensity}$  value in the next 12 quarters as an alternative control for future expectations, and again find a significant negative coefficient on investment. Finally, in column (4) we add the category-specific measures and find statistically significant negative effects for the Healthcare EPU index and the Financial Regulation EPU index. That is, the frequency of newspaper articles about these types of policy uncertainty has additional explanatory power for the investment rates of firms that operate in sectors most affected by these types of policy.

Columns (5) to (8) investigate the effect of EPU on annual firm-level rate employment growth rates. (Compustat lacks quarterly employment data.) As with investment rates, we find sizable and statistically significant negative effects of policy uncertainty on employment growth rates for firms with high exposure to government policy. Consider again an 84 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  $\log(\text{EPU}) \times \text{Intensity}$  in Column (5) implies a drop in the annual employment growth rate of 4.5 percentage points. The only qualitative difference between the investment rate and employment growth results involves the category-specific EPU variables. They are statistically insignificant in the employment growth regression except for  $(\text{Financial Regulation EPU}) \times \text{Intensity}$ , which has a positive coefficient that is significant at the 10% level. Taken at face value, this potentially surprising result suggests that greater uncertainty about financial regulatory policy post 2008 raised employment at firms in the financial industry.

Finally, 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  $\log(\text{EPU}) \times \text{Intensity}$  in column (9) is negative but not statistically significant, while the  $(\text{Federal Purchases}/\text{GDP}) \times \text{Intensity}$  variable remains positive and significant. Hence, our results suggest that policy uncertainty

reduces near-term investment and employment for firms in policy-exposed sectors, but the near-term impact on their output levels is more limited.

#### **4.2 Policy Uncertainty and Aggregate Economic Activity**

As an alternative approach to evaluating the economic effects of policy uncertainty, we now consider VAR models that exploit time-series variation at the country level. Drawing causal inferences from VARs is challenging, in part because policy – and policy uncertainty – can respond to current and future economic conditions. Despite the challenges, VARs are useful for characterizing dynamic relationships, and they provide information about the magnitude of policy uncertainty effects under certain identifying assumptions. At a minimum, VARs let us gauge whether policy uncertainty shocks foreshadow weaker macroeconomic performance conditional on standard macro and policy variables.

We start by fitting a VAR to monthly US data from January 1985 to December 2012. To recover orthogonal shocks, we use a Cholesky decomposition with the following ordering: the EPU index, the log of the S&P 500 index, the federal funds rate, log employment, and log industrial production. Our baseline VAR specification includes three lags of all variables. Figure 8 depicts the model-implied responses of industrial production and employment to a 90-point EPU innovation, equal in size to the EPU index change from its average value in 2005-06 (before the financial crisis and recession) to its average value in 2011-12 (a period with major fiscal policy battles and high EPU levels). Figure 8 shows maximum estimated drops of 1.2% in industrial production and 0.35% in employment. These responses are statistically significant and moderate in size, being about one-third as large as a typical business cycle fluctuation. Since aggregate US investment data are not available at a monthly frequency, we also estimated an analogous VAR model on quarterly data from 1985 to 2012, using the same type of Cholesky decomposition to identify shocks. As shown in Appendix Figure C6, gross aggregate investment exhibits a peak decline of about 6% in response to a 90-point EPU innovation.

Figure 9 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 very much 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 mitigates this concern, given that stock markets are forward looking and that stock prices incorporate many sources of information. Our baseline VAR also includes other “first-moment” variables: log employment, log industrial production, and the fed funds rate. Still, the EPU index may embed first-moment information not captured by these variables. To investigate this issue, we also considered VARs that include the Michigan Consumer Sentiment Index.<sup>26</sup> When we place the Michigan index after the EPU index in the causal ordering, the estimated peak effect of a policy uncertainty shock on industrial production falls by about one-third (Appendix Figure C7). When we place the Michigan index first in the causal ordering, the peak effect shrinks by about half. These results indicate that, conditional on the other variables, our EPU index and the Michigan index contain overlapping information that has value for predicting future output and employment movements.

Perhaps this result is unsurprising. The Michigan index captures a mix of first-moment and second-moment concerns, as expressed by households in survey data. The relationship between “confidence” and uncertainty is a murky one, and the two concepts are tightly linked at a deep level in some theoretical models, e.g., Ilut and Schneider (2014). In any event, the EPU index has several important advantages relative to consumer confidence indices: EPU indices can be extended to many countries, pushed back in time by a century or more in some countries, computed in near real-time on a daily basis, and parsed in many ways as illustrated by our category-specific EPU indices.

Figure 10 shows impulse response functions for a panel VAR fit to monthly data from 1985 to 2012 on the twelve countries for which we have an EPU index. The panel VAR specification parallels the baseline specification that underlies Figure 8, except that we use the

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<sup>26</sup> The Michigan index reflects phone surveys of consumers and seeks to determine how consumers view the short-term economy, the long-term economy, and their own financial situation. It takes the difference between the percent answering positively and the percent answering negatively for each of 5 questions, then averages these differences and normalizes by the base period (December 1968) total. The Michigan index has a correlation of -0.742 with our EPU index. We chose the Michigan index as the more commonly used consumer confidence index, but other consumer confidence indices are highly correlated with the Michigan Index – for example, the Bloomberg Confidence index has a correlation of 0.943 with the Michigan index, and the Conference Board Confidence index has a correlation of 0.912 with the Michigan index.

unemployment rate in place of  $\log(\text{employment})$ . As before, we rely on a Cholesky decomposition to identify shocks and display responses to a 90-point EPU innovation, which is well within the range of EPU movements experienced by the individual countries. The twelve-country panel VAR yields results that are similar to the US results in Figure 8. In particular, the international panel VAR implies that a 90-point EPU innovation foreshadows a peak drop in industrial production of about 1 percent and a rise in the unemployment rate of about 25 basis points. Appendix Figure C8 shows that the basic character of the panel VAR results is robust to a variety of alternative specifications, variable sets, and weighting methods. Other researchers who use our EPU indices in multi-country time-series analyses also find that policy uncertainty shocks foreshadow deteriorations in macroeconomic outcomes (IMF, 2013).

## 5. CONCLUSION

We develop new measures of economic policy uncertainty for the United States and eleven other major economies. We use these new measures to investigate the effects of policy uncertainty on firm-level stock price volatility implied by equity options, firm-level investment rates and employment growth rates and on aggregate investment, output and employment. Our findings are broadly consistent with theories that highlight negative economic effects of uncertainty shocks. The magnitudes of our estimated effects suggest that elevated policy uncertainty in the United States and Europe in recent years had material harmful effects on macroeconomic performance.

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. As illustrated by our category-specific EPU indices and annotated charts, newspapers also offer much potential for assessing the role of specific developments and shocks, at least as perceived by contemporary observers.

## References

- Alexopoulos, Michelle and Jon Cohen, 2015. "The Power of Print: Uncertainty Shocks, Markets, and the Economy," *International Review of Economics and Finance*, forthcoming.
- Azzimonti, Marina, 2015. "Partisan Conflict and Private Investment," NBER Working Paper 21723.
- Bachmann, Rüdiger, Steffen Elstener, and Eric Sims, 2013. "Uncertainty and Economic Activity: Evidence from Business Survey Data," *American Economic Journal: Macroeconomics*, 5, no. 2 (May), 217-249.
- Baker, Scott, Nicholas Bloom, Brandice Canes-Wrone, Steven J. Davis and Jonathan Rodden, 2014. "Why Has US Policy Uncertainty Risen Since 1960?" *American Economic Review, Papers & Proceedings*, 104, no. 5 (May), 56-60.
- Baker, Scott, Bloom, Nicholas and Davis, Steven J., 2015. "What triggers stock market jumps?" Work in progress presented at the January 2015 ASSA meetings.
- Basu, Susanto and Brent Bundick (2014), "Uncertainty shocks in a model of effective demand", NBER working paper 18420.
- Belo, Federico, Vito D. Gala and Jun Li, 2013. "Government Spending, Political Cycles, and the Cross Section of Stock Returns," *Journal of Financial Economics*, 107, no 2, 305-324.
- Bernanke, Ben S., 1983. "Irreversibility, Uncertainty and Cyclical Investment," *Quarterly Journal of Economics*, 97, no. 1 (February), 85-106.
- Bloom, Nicholas, 2009. "The Impact of Uncertainty Shocks," *Econometrica*, 77 no. 3 (May), 623-685.
- Bloom, Nicholas, Stephen Bond, and John van Reenen, 2007. "Uncertainty and Investment Dynamics," *Review of Economic Studies*, 74, 391-415.
- Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta and Stephen Terry, 2014. "Really Uncertain Business Cycles," working paper, Stanford.
- Born, Benjamin and Johannes Pfeifer, 2014. "Policy Risk and the Business Cycle," *Journal of Monetary Economics*, 68 (November), 68-85.
- Boudoukh, Jacob, Ronen Feldman, Shimon Kogan, and Matthew Richardson, 2013. "Which News Moves Stock Prices? A Textual Analysis" NBER Working Paper 18725.
- Brogaard, Jonathan and Andrew Detzel, 2015. "The Asset Pricing Implications of Government Economic Policy Uncertainty," *Management Science*, 61, no. 1 (January), 3-18.
- Campbell, John L., Hsinchun Chen, Dan S. Dhaliwal, Hsin-min Lu and Logan B. Steele, 2014. "The Information Content of Mandatory Risk Factor Disclosures in Corporate Filings," *Review of Accounting Studies*, 19, 396-455.
- Chicago Board Options Exchange, 2004. "VIX CBOE Volatility Index," White Paper.
- Davis, Steven J., John Haltiwanger, Ron Jarmin and Javier Miranda 2007. "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms," *NBER Macroeconomics Annual*, 21, 107-180.
- Dixit, Avinash K. and Robert S. Pindyck, 1994. *Investment Under Uncertainty*. Princeton, NJ: Princeton University Press.
- Durnev, Art, 2010. "The Real Effects of Political Uncertainty: Elections and Investment Sensitivity to Stock Prices," working paper, McGill University, September.
- Fernandez-Villaverde, Jesus, Pablo Guerron-Quintana, Keith Kuester, and Juan Rubio-Ramirez, 2015. "Fiscal volatility shocks and economic activity," *American Economic Review*, forthcoming.

- Friedman, Milton, 1968. "The Role of Monetary Policy," *American Economic Review*, 58, no. 1 (March), 1-17.
- Federal Open Market Committee, 2009. Minutes of the December 2009 Meeting, <http://www.federalreserve.gov/monetarypolicy/fomcminutes20091216.htm>.
- Gentzkow, Matthew and Jesse M. Shapiro, 2010. "What Drives Media Slant? Evidence from US Daily Newspapers," *Econometrica* 78, no. 1 (January), 35-71.
- Giavazzi, Francesco and Michael McMahon, 2012. "Policy Uncertainty and Household Savings," *Review of Economics & Statistics*, 94, no. 2 (May), 517-531.
- Gilchrist, Simon, Jae W. Sim and Egon Zakrajsek, 2014. "Uncertainty, Financial Frictions, and Investment Dynamics," NBER Working Paper 20038.
- Gulen, Huseyin and Mihai Ion, 2015. "Policy uncertainty and corporate investment," working paper, Purdue University.
- Handley, Kyle and Nuno Limao, 2012. "Trade and Investment under policy uncertainty: Theory and Firm Evidence," *American Economic Journal: Policy*, forthcoming.
- Hassett, Kevin A. and Gilbert E. Metcalf, 1999. "Investment with Uncertain Tax Policy: Does Random Tax Policy Discourage Investment?" *Economic Journal*, 109, no. 457 (July), 372-393.
- Higgs, Robert, 1997, "Regime Uncertainty: Why the Great Depression Lasted So Long and Why Prosperity Resumed After the War," *The Independent Review*, 1, no. 4 (Spring), 561-590.
- Hoberg, Gerard, and Gordon Phillips, 2010. "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis." *Review of Financial Studies*, 23, no. 10, 3773-3811.
- Ilut, Cosmin and Martin Schneider, 2014. "Ambiguous Business Cycles," *American Economic Review*, 104, no. 8, 2368-2399.
- International Monetary Fund, 2012, "World Economic Outlook: Coping with High Debt and Sluggish Growth", October, IMF Press.
- International Monetary Fund, 2013, "World Economic Outlook: Hopes, Realities, Risks," April, IMF Press.
- Julio, Brandon and Youngsuk Yook, 2012. "Political Uncertainty and Corporate Investment Cycles," *Journal of Finance*, 67, no. 1 (February), 45-83.
- Jurado, Kyle, Ludvigson, Sydney and Ng, Serena, 2015. "Measuring Uncertainty," *American Economic Review*, 105, no.3 (March), 1177-1216.
- Kelly, Bryan, 2015. "The Price of Political Uncertainty: Theory and Evidence from the Option Market," *Journal of Finance*, forthcoming.
- Leduc, Sylvain and Zheng Liu, 2015. "Uncertainty Shocks Are Aggregate Demand Shocks," Federal Reserve Bank of San Francisco working paper, May.
- Nalewaik, Jeremy, 2015. "Regime-Switching Models for Estimating Inflation Uncertainty," working paper, Board of Governors of the Federal Reserve System, August.
- Panousi, Vasia and Dimitris Papanikolaou, 2012. "Investment, idiosyncratic risk and ownership," *Journal of Finance*, 67, no. 3 (June), 1113-1148.
- Pastor, Lubos and Pietro Veronesi, 2012. "Uncertainty about Government Policy and Stock Prices," *Journal of Finance*, 67, no. 4 (August), 1219-1264.
- Pastor, Lubos and Veronesi, Pietro, 2013. "Political Uncertainty and Risk Premia," *Journal of Financial Economics*, 110, no. 3 (December), 520-545.
- Rodrik, Dani, 1991. "Policy Uncertainty and Private Investment," *Journal of Development Economics*, 36, no. 2 (October), 229-242.

- Scotti, Chiara, 2014. "Surprise and Uncertainty Indexes: Real-Time Aggregation of Real-Activity Macro Surprises," working paper, Federal Reserve Board.
- Shoag, Daniel and Stan Veuger, 2015. "Uncertainty and the Geography of the Great Recession," AEI Economic Policy Working Paper 2015-07.
- Stock, James and Mark Watson. 2012. "Disentangling the Channels of the 2007-2009 Recession," *Brookings Panel on Economic Activity*, Spring, 81-135.

**Table 1: Economic Policy Uncertainty by Policy Category and Time Period, 1985 to 2014**

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

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

**Table 2: Firm-Level Effects of Policy Uncertainty on Option-Implied Stock Price Volatility**

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

**Notes:** The sample contains 136,742 observations on 5,624 firms from 1996 to 2012. The dependent variable is the 30-day implied volatility for the firm, averaged over all days in the quarter. **Intensity** is the firm's exposure to federal government purchases of goods and services computed by the two-step method described in Section 4. **Federal Purchases/GDP** is from NIPA tables. **Log(EU)** is the log of the newspaper-based Economic Uncertainty index. **Defense EPU\*Defense Firm** is the National Security EPU index from Table 1 multiplied by 1 for firms in the defense industry (SICs 348, 372, 376, 379, 381 and 871) and 0 otherwise, and analogously for **Healthcare EPU\*Health Firm** (SICs 800 to 809) and **Finance EPU\*Finance Firm** (SICs 600 to 699). All regressions weighted by average sales of the firm during the sample period. Standard errors based on clustering at the firm level.

**Table 3: Robustness Checks for Firm-Level Effects of Policy Uncertainty on Option-Implied Stock Price Volatility**

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
<b>Log(EPU)×Intensity</b>	0.346*** (0.089)	0.178*** (0.073)	0.175*** (0.070)	0.258*** (0.086)	0.192*** (0.045)	0.456*** (0.101)	0.283** (0.118)	0.378* (0.217)	0.237*** (0.071)
<b>(Federal Purchases/ GDP)×Intensity</b>	-23.72 (14.71)	-27.47*** (11.77)	-58.28*** (15.35)	-7.05 (16.74)	-14.20 (10.03)	-13.60 (27.64)	6.157 (14.97)	27.16 (64.17)	-31.03 (12.40)
<b>(Forecasted Federal Purchases/GDP)×Intensity</b>			32.61*** (6.27)						
<b>Firm and Time Effects</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>	<b>Yes</b>
<b>Observations</b>	136,742	136,742	136,742	73,822	136,742	134,544	133,465	112,123	42,785
<b>Number of Firms</b>	5,624	5,624	5,624	3,189	5,624	5,537	5,489	3,817	1,070

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

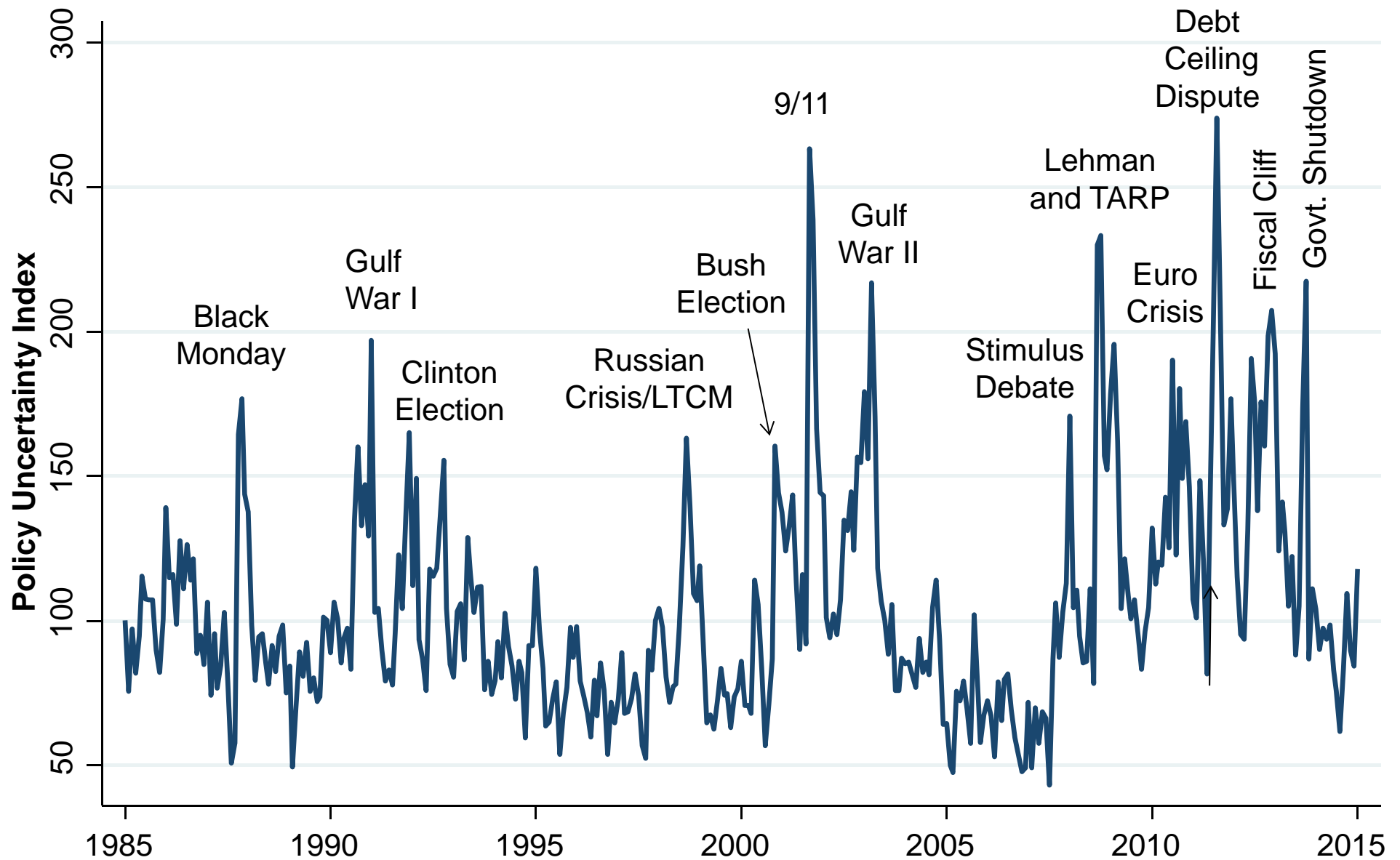


**Table 4: Cross-Firm Effects of Policy Uncertainty on Investment Rates and Employment Growth Rates**

<b>Dependent Variable:</b>	<b>(1)</b> I/K	<b>(2)</b> I/K	<b>(3)</b> I/K	<b>(4)</b> I/K	<b>(5)</b> $\Delta$ Emp	<b>(6)</b> $\Delta$ Emp	<b>(7)</b> $\Delta$ Emp	<b>(8)</b> $\Delta$ Emp	<b>(9)</b> $\Delta$ Rev
<b>Log(EPU)×Intensity</b>	-0.032*** (0.010)	-0.032*** (0.010)	-0.024** (0.011)	-0.031*** (0.010)	-0.213** (0.084)	-0.227** (0.089)	-0.220** (0.118)	-0.207** (0.084)	-0.128 (0.096)
<b><math>\Delta</math>(Federal Purchases/ GDP)×Intensity</b>	8.20*** (2.86)	8.04*** (2.86)	12.12*** (3.18)	8.23*** (2.87)	10.79 (7.41)	15.60*** (8.04)	3.19 (12.56)	11.58 (7.58)	20.39** (9.43)
<b><math>\Delta</math>(Forecasted Federal Purchases/GDP)×Intensity</b>		1.01 (0.828)				-4.65*** (2.89)			
<b>Defense EPU × Defense Firm</b>				0.094 (0.314)				-2.53 (1.60)	
<b>Healthcare EPU × Health Firm</b>				-0.422* (0.231)				1.16 (1.42)	
<b>Financial Regulation EPU × Finance Firm</b>				-0.270*** (0.076)				0.636* (0.353)	
<b>Periodicity</b>	Quarterly	Quarterly	Quarterly	Quarterly	Yearly	Yearly	Yearly	Yearly	Yearly
<b>3 Years Fed Exp leads</b>	No	No	Yes	No	No	No	Yes	No	No
<b>Observations</b>	709,120	709,120	411,832	709,120	162,006	162,006	108,718	162,006	151,653
<b>Number of Firms</b>	22,358	22,358	14,190	22,358	17,151	17,151	13,018	17,151	15,929

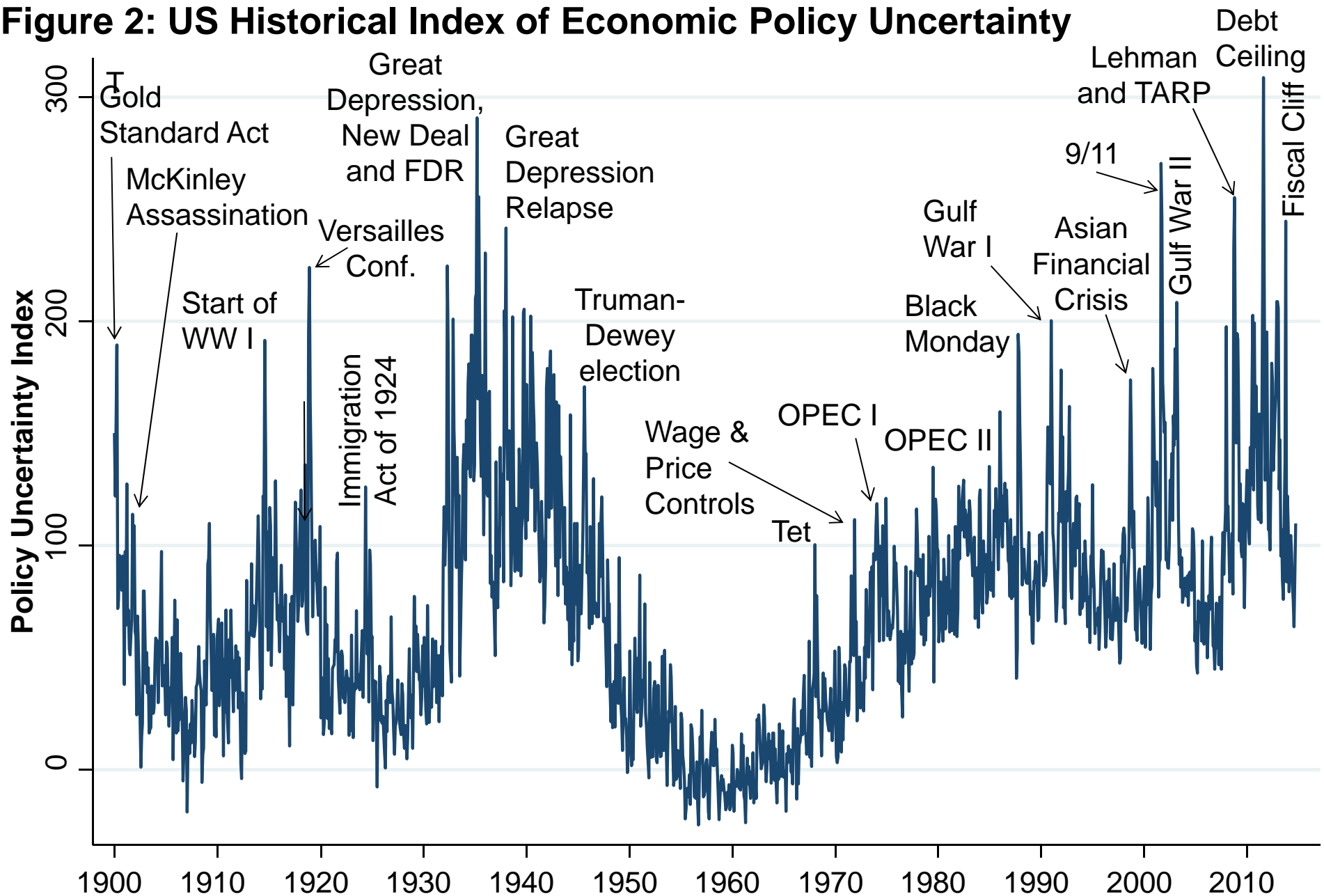
**Notes:** The sample period runs from 1985 to 2012. All columns include a full set of firm and time effects. **I/K** is the investment rate defined as  $\text{CapEx}_t/(\text{Net Plant, Property and Equipment})_{t-1}$ .  **$\Delta$ Emp** is the employment growth rate measured as  $(\text{emp}_t - \text{emp}_{t-1})/(0.5 \times \text{emp}_t + 0.5 \times \text{emp}_{t-1})$ , and  **$\Delta$ Rev** is the corresponding revenue growth rate.  **$\Delta$ (Federal Purchases/GDP)×Intensity** is the change in (Federal Purchases/GDP) from NIPA tables in the next quarter in quarterly specifications and in the next year in annual specifications, multiplied by the firm-level policy exposure intensity variable.  **$\Delta$ (Forecast Federal Purchases/GDP)×Intensity** instead uses the mean forecasted change in (Federal Purchases/GDP), drawing on NIPA data for the current values and forecast data for the future values. See the notes to Table 2 for additional variable definitions. For presentation purposes, we scale the point estimates and standard errors by 100 for the variables involving category-specific EPU terms. Standard errors based on clustering at the firm level.

**Figure 1: Economic Policy Uncertainty Index for the US, 1985 to 2014**



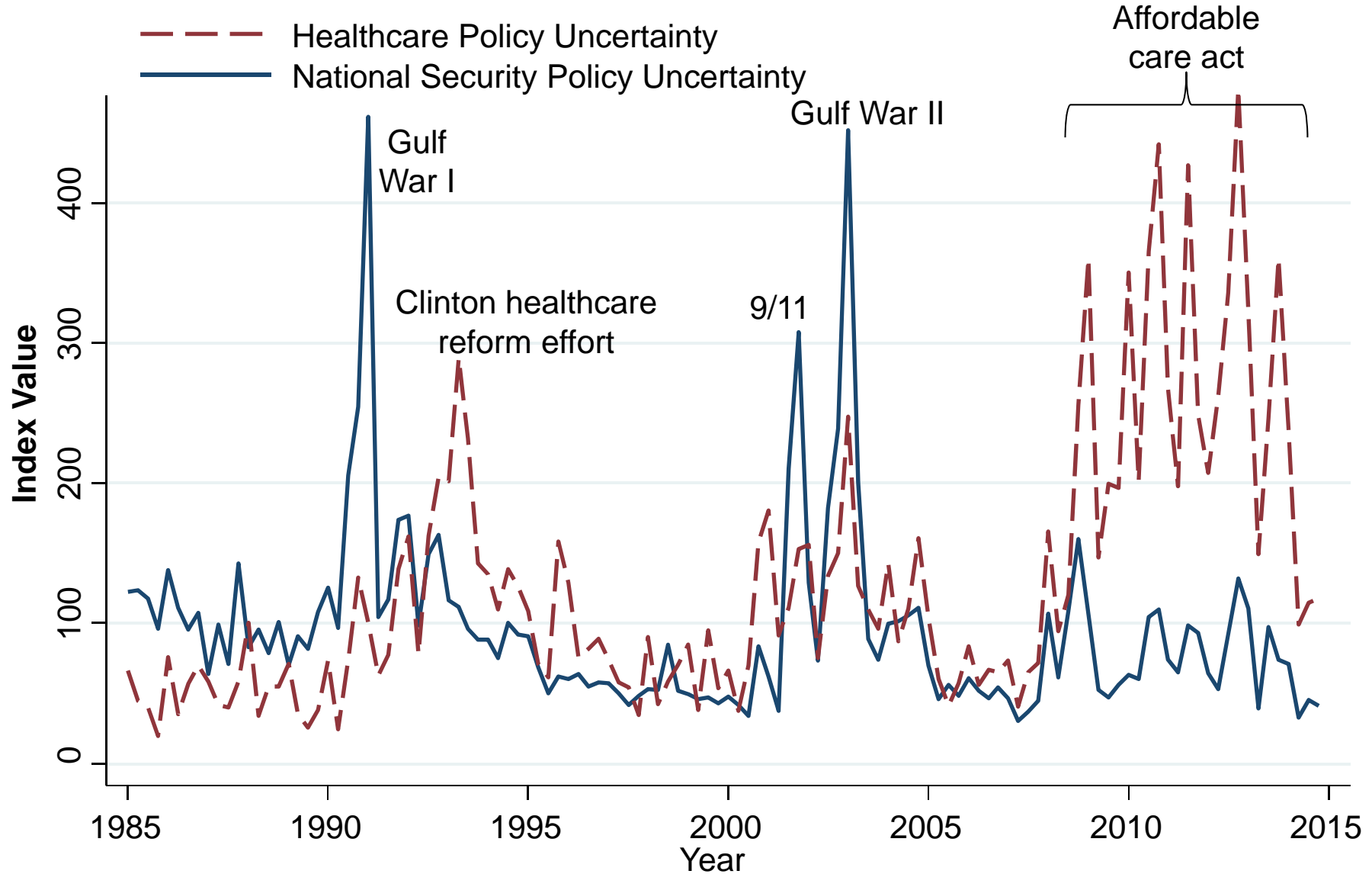
**Notes:** Index reflects scaled monthly counts of articles containing 'uncertain' or 'uncertainty', 'economic' or 'economy', and one or more policy relevant terms: 'regulation', 'federal reserve', 'deficit', 'congress', 'legislation', or 'white house'. The series is normalized to mean 100 from 1985-2009 and based on queries run on 2 February, 2015 for the USA Today, Miami Herald, Chicago Tribune, Washington Post, LA Times, Boston Globe, SF Chronicle, Dallas Morning News, NY Times, and the Wall Street Journal.

**Figure 2: US Historical Index of Economic Policy Uncertainty**



**Notes:** 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 1, 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 3: National Security and Healthcare EPU Indices, 1985 to 2014**



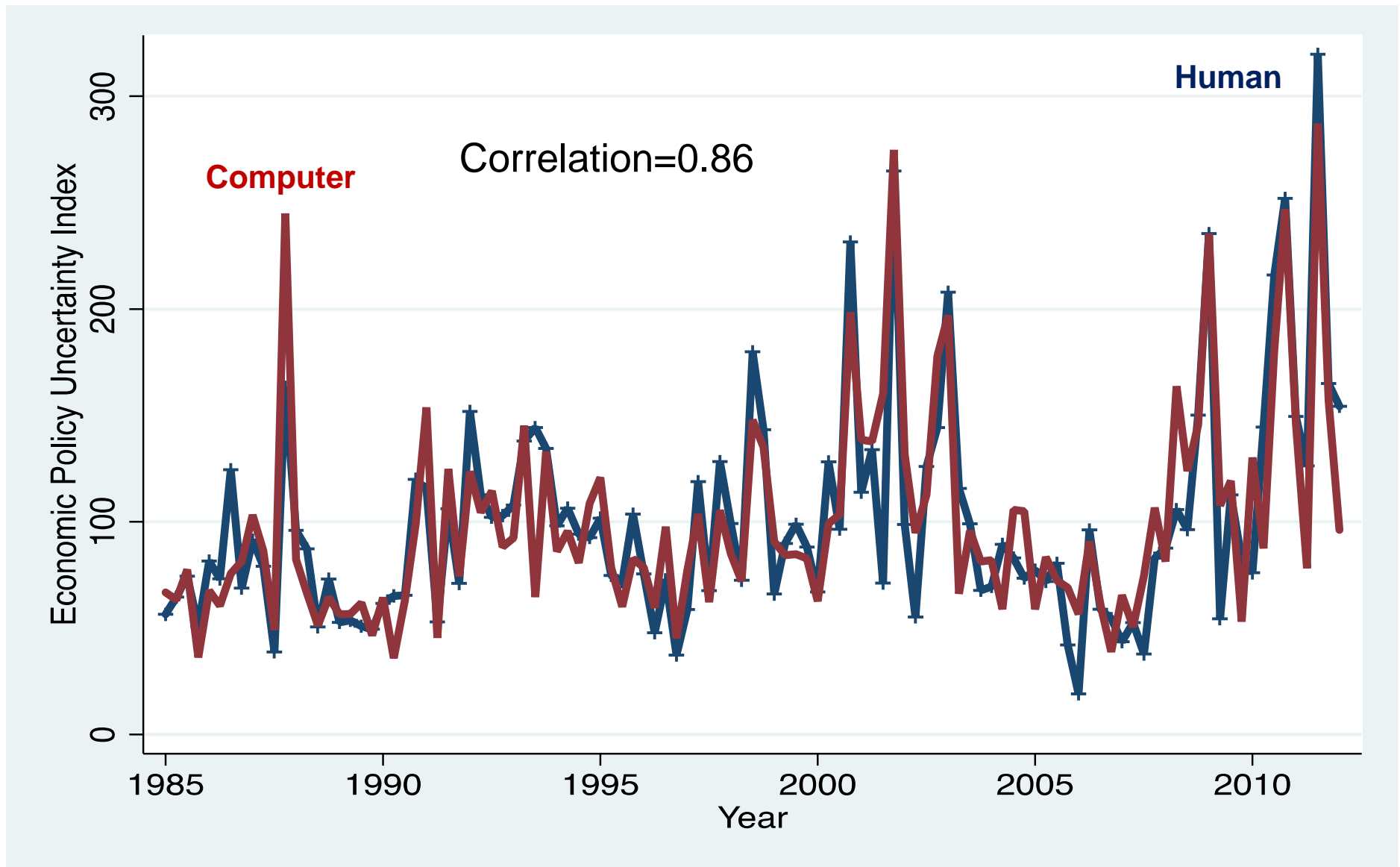
**Notes:** Indices reflect scaled monthly counts of articles containing the same triple as in Figure 1 **and** one or more terms pertaining to national security (e.g., “war”, “terrorism”, or “department of defense”) and healthcare (e.g., “healthcare”, “hospital”, or “health insurance”), respectively, 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 4: Index of Economic Policy Uncertainty for Russia



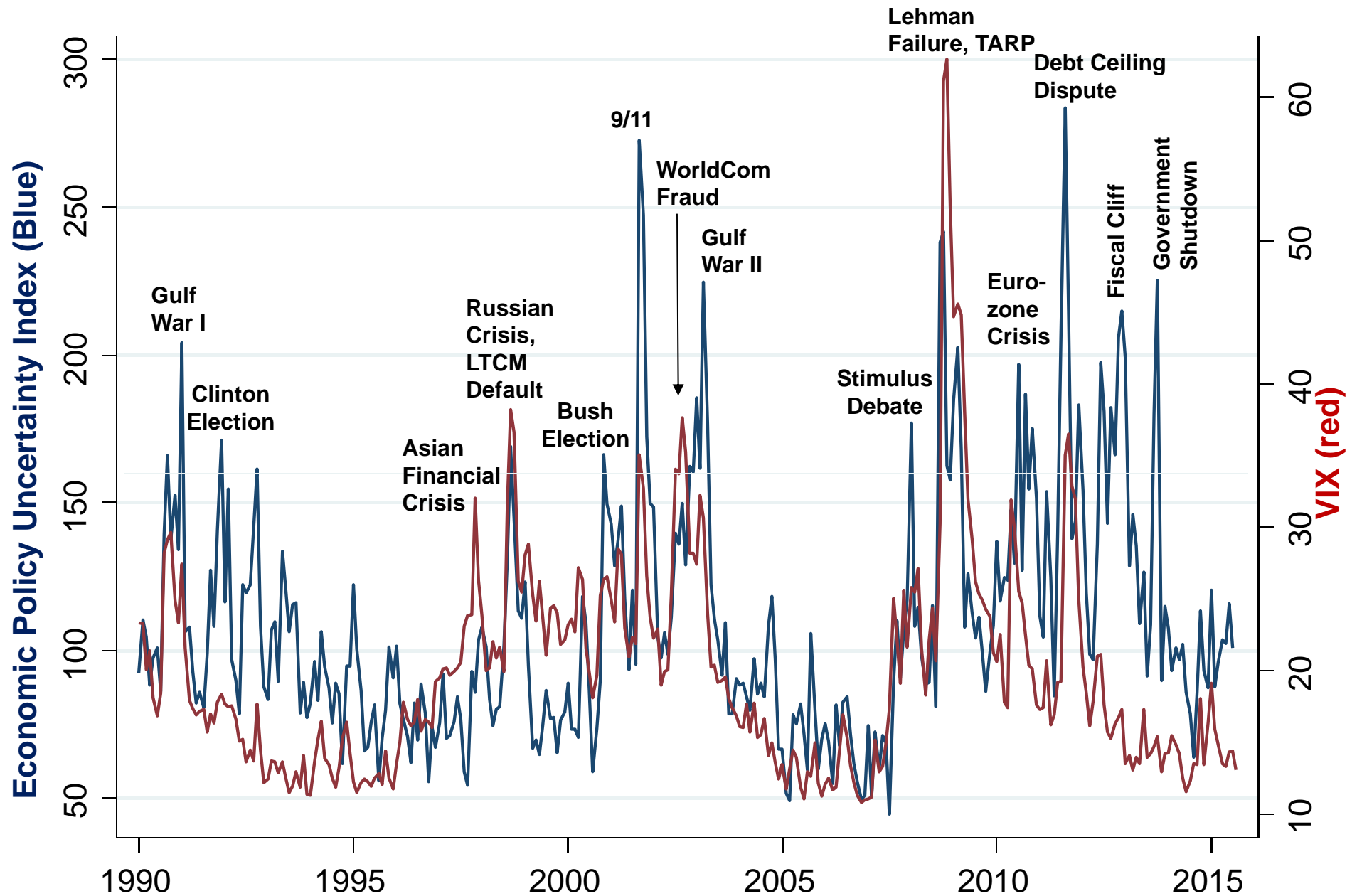
Index reflects scaled monthly counts of articles in Kommersant with Russian terms for 'uncertain' or 'uncertainty', 'economic' or 'economy', and one or more selected policy terms. The series is normalized to 100 and runs from October 1992 to August 2014.

**Figure 5: Human and Computer EPU Indices, 1985 to 2012, Quarterly**



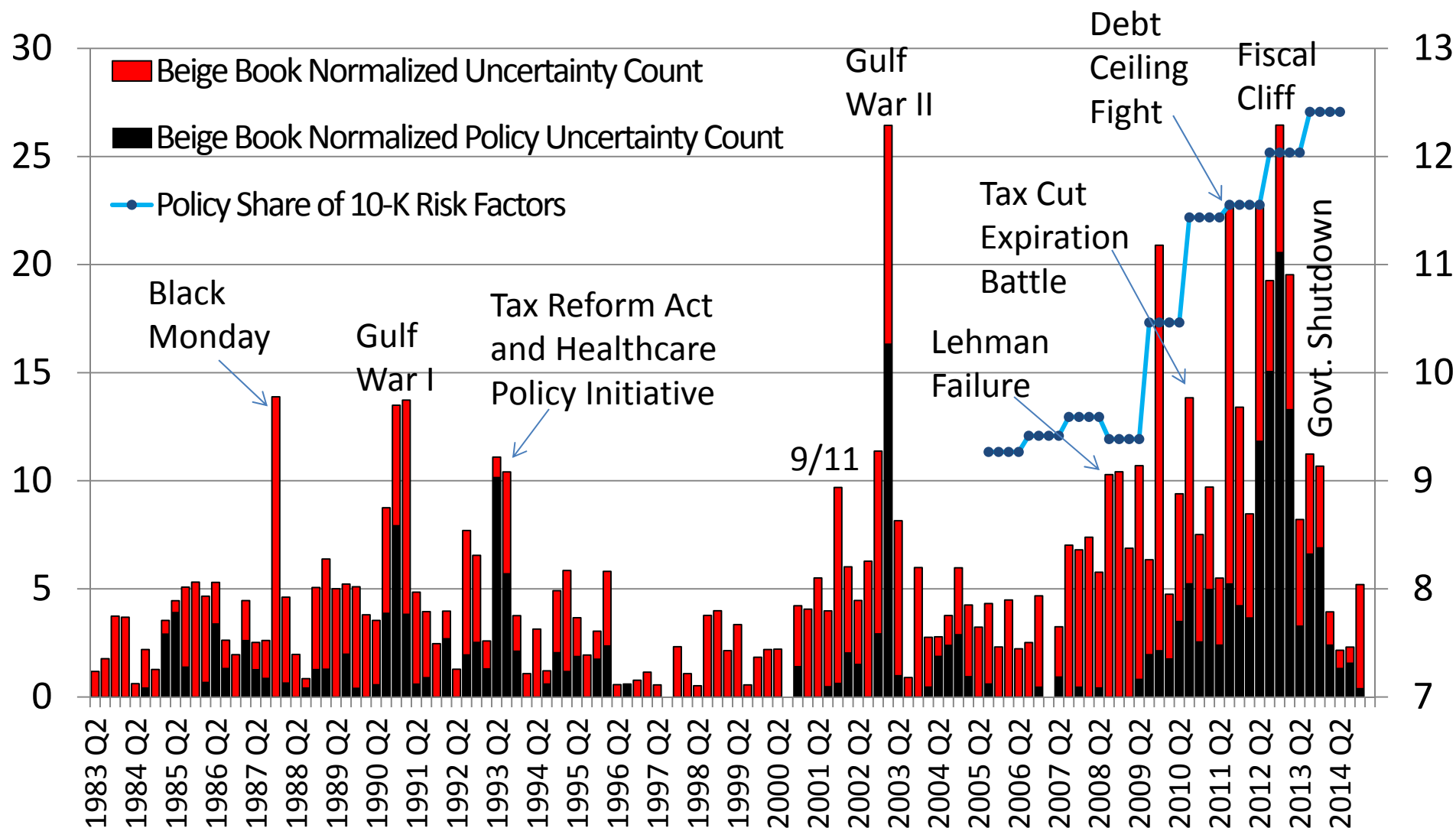
**Notes:** Index comparison from 1985 Q1 to 2012 Q1 based on 3,723 articles (4,388 audits) in the Chicago Tribune, Dallas Morning News, LA Times, Miami Herald, NY Times, San Francisco Chronicle, Washington Post and Wall Street Journal. Series are plotted quarterly to reduce sampling variability, with 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 6: U.S. EPU Compared to 30-Day VIX, January 1990 to July 2015**



Notes: The figure shows the U.S. EPU Index from Figure 1 and the monthly average of daily values for the 30-day VIX.

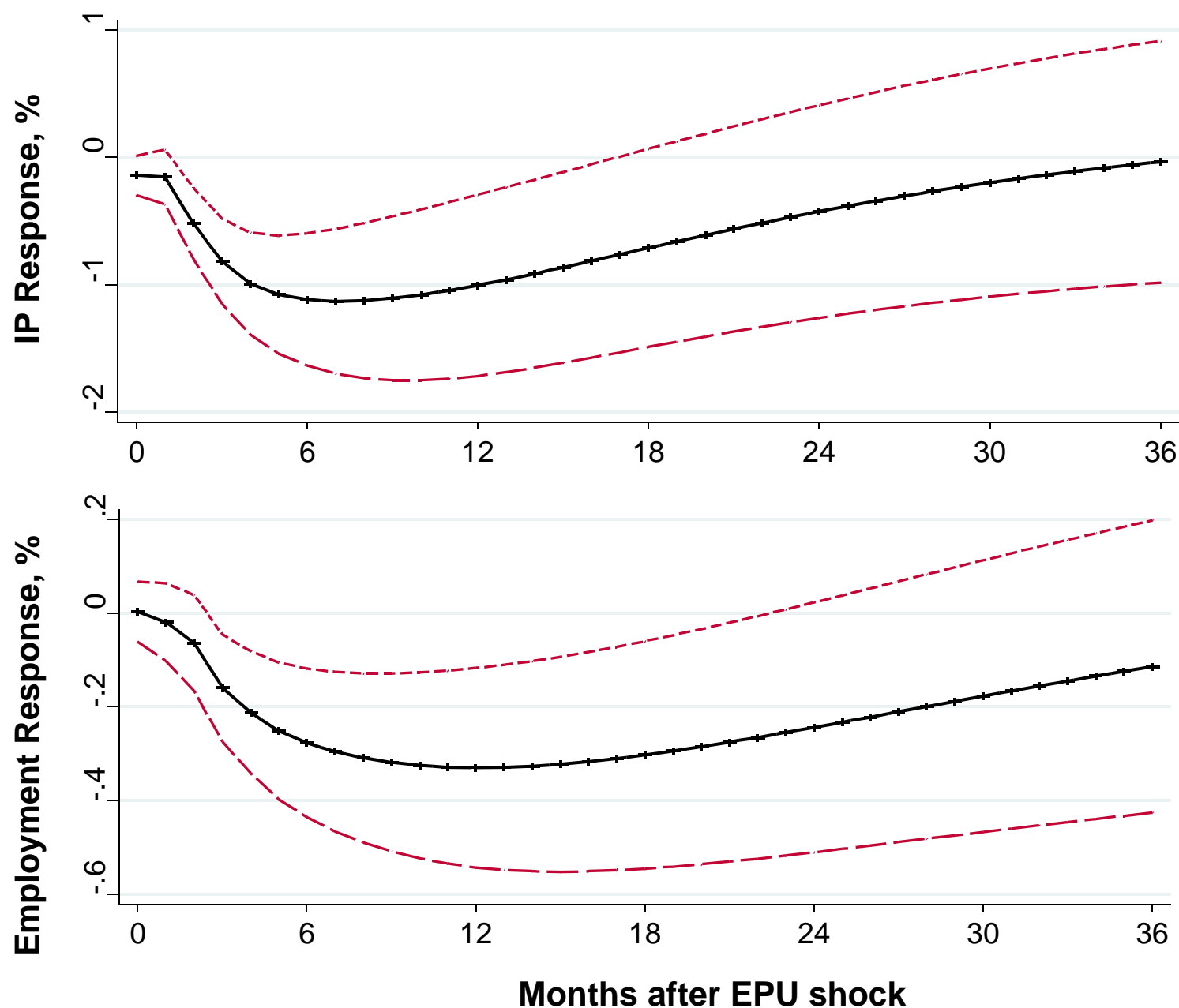
**Figure 7: Policy Uncertainty Measures Based on Textual Analysis of the Fed's Beige Books and Section 1A (Risk Factors) of Firms' 10K Filings**



Notes: 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 Section 1A (Risk Factors) of annual 10-K filings that contain one or more of the policy terms listed in Appendix C. The correlation between the Beige Book Normalized Policy Uncertainty Count and the EPU index is 0.54.

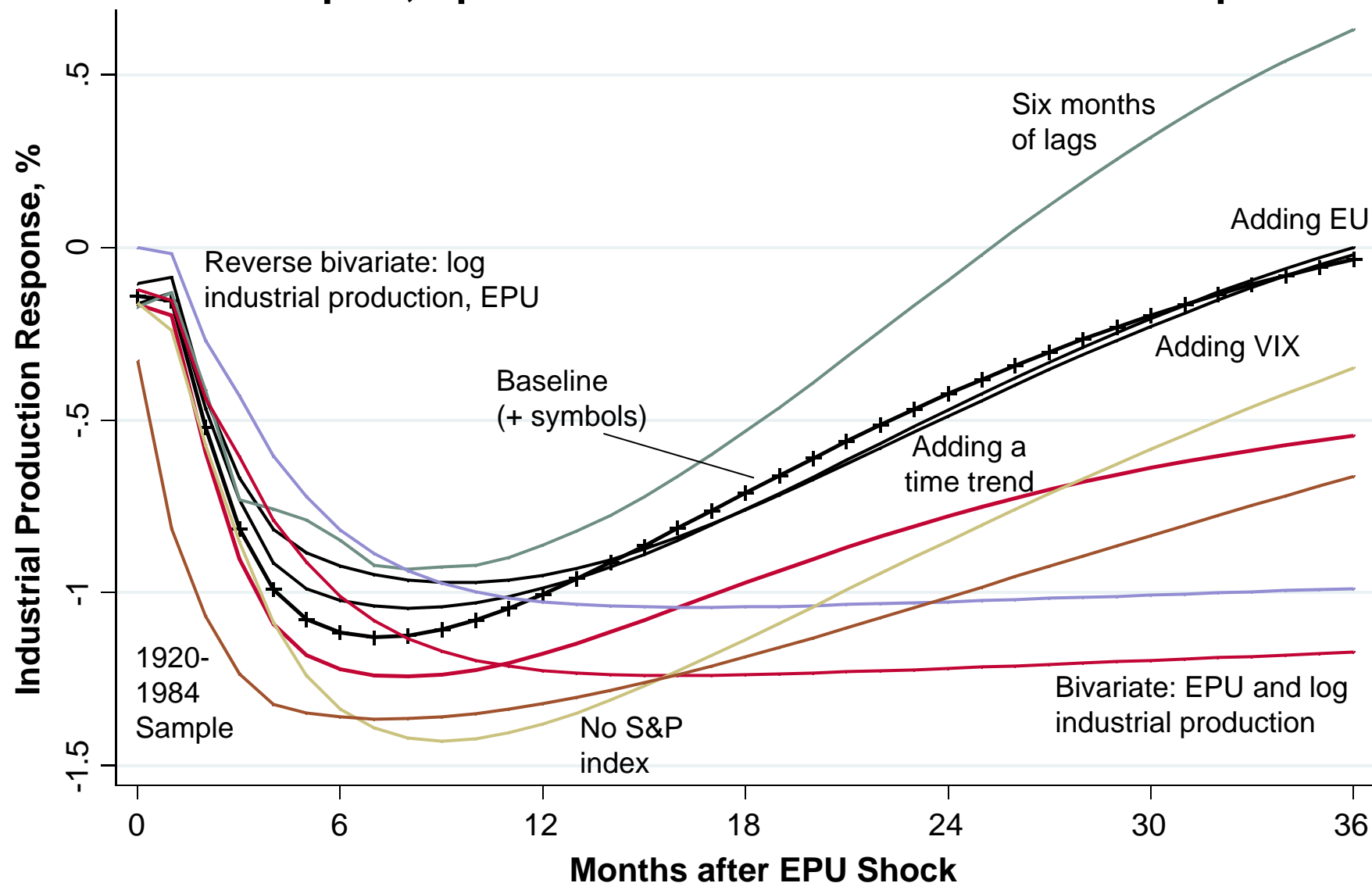


**Figure 8: Industrial Production and Employment Responses to EPU Shock, VAR Fit to Monthly U.S. Data from January 1985 to December 2012**



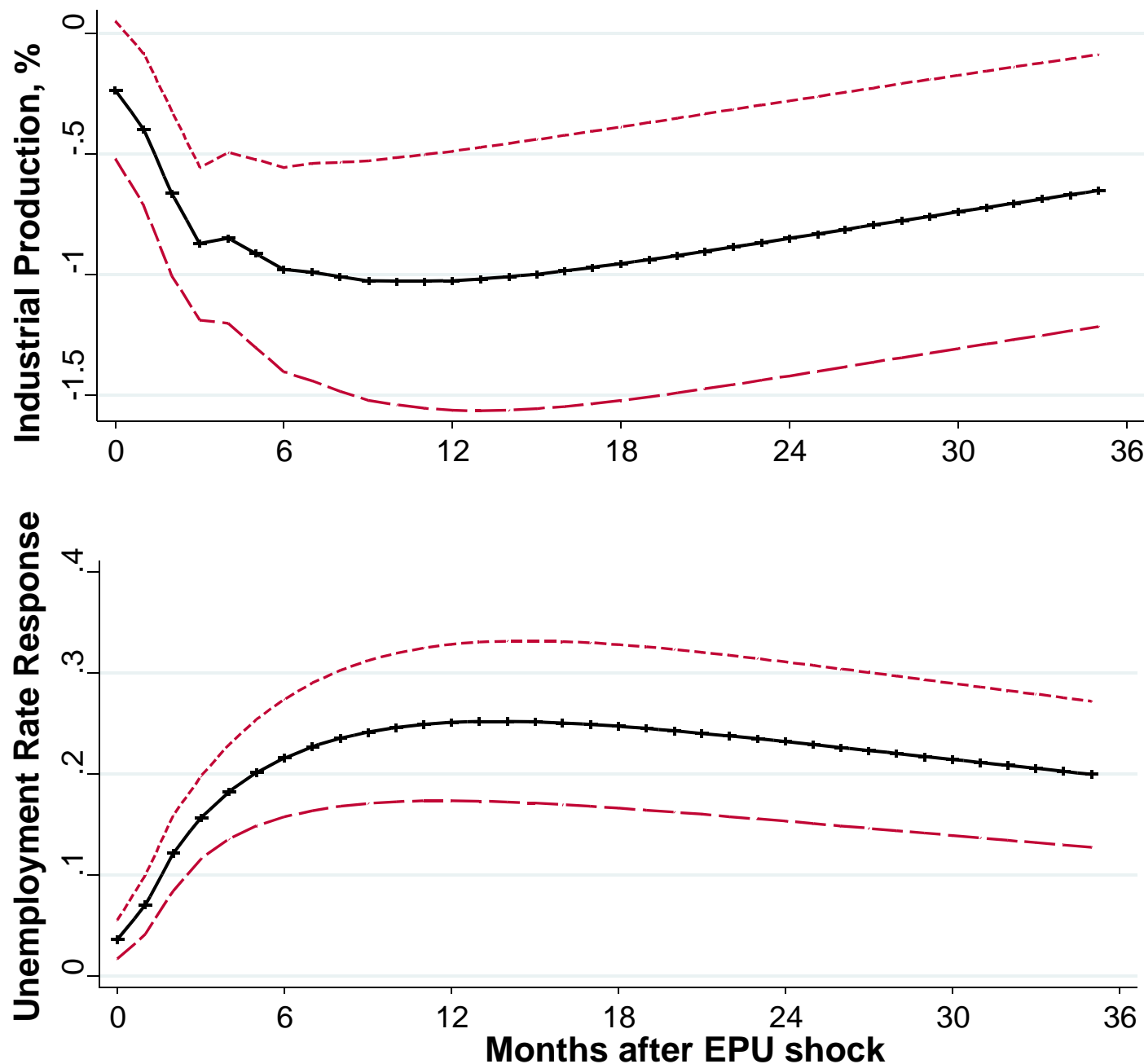
**Notes:** VAR-estimated impulse response functions for industrial production and employment to an EPU innovation equal to the increase in the EPU index from its 2005-2006 to its 2011-2012 average value, with 90 percent confidence bands. Identification based on three lags and a Cholesky decomposition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

**Figure 9: U.S. Industrial Production Response to an EPU Shock, Alternative Samples, Specifications and Identification Assumptions**



**Notes:** The baseline case involves the same sample period, VAR specification and identification as in Figure 8. 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 10: Responses to an EPU Shock in a Twelve-Country Panel VAR



**Notes:** Panel-VAR estimated impulse response functions for industrial production and unemployment to an EPU innovation equal to the increase in the average US EPU value from 2005-2006 to 2011-2012, with 90% confidence bands. Identification based on three lags and a Cholesky decomposition with the following ordering: EPU index, log(stock market index), unemployment rate, and log industrial production. We use own-country data and a full set of country fixed-effects in the panel VAR. Country-level data are weighted by the square root of the number of newspapers used in the EPU index. Fit to monthly data for Canada, China, France, Germany, India, Italy, Japan, Korea, Russia, Spain, UK and the US from January 1985 to December 2012, where available.

## Appendix

### A. Newspapers, Archives, and EPU Term Sets

United States (1985-, monthly): We search the LA Times, USA Today, Chicago Tribune, Washington Post, Boston Globe, and Wall Street Journal using Proquest newspaper archives; the Miami Herald, Dallas Morning News, Houston Chronicle, and San Francisco Chronicle using the Access World News Newsbank service; and the New York Times using its own online archive. Because the New York Times archive occasionally yields unstable article counts for recent dates, we replaced the Times with the Houston Chronicle as of January 2014. In particular, after rescaling the Chronicle's EPU index to match the mean and variance of the Times prior to 2014, we use EPU values from the Chronicle instead of the Times from January 2014 onwards in constructing our 10-paper monthly index. The full set of policy terms is regulation, deficit, legislation, congress, white house, Federal Reserve, the Fed, regulations, regulatory, deficits, congressional, legislative, and legislature. Section 3.1 in the main text explains how we selected this term set.

Let  $X_{it}$  denote the scaled EPU frequency country for newspaper  $i=1, 2, \dots, 10$  in month  $t$ , and let  $T_1$  and  $T_2$  denote the time intervals used in the standardization and normalization calculations. For the United States, both  $T_1$  and  $T_2$  cover the period from January 1985 to December 2009. To aggregate over newspapers and construct our monthly US EPU index, we proceed in the following steps: (1) Compute the times-series variance,  $\sigma_i^2$ , in the interval  $T_1$  for each paper  $i$ . (2) Standardize  $X_{it}$  by dividing through by the standard deviation  $\sigma_i$  for all  $t$ . This operation yields, for each paper, a series  $Y_{it}$  with unit standard deviation in the interval  $T_1$ . (3) Compute the mean over newspapers of  $Y_{it}$  in each month  $t$  to obtain the series  $Z_t$ . (4) Compute  $M$ , mean value of  $Z_t$  in the interval  $T_2$ . (5) Multiply  $Z_t$  by  $((100 / M))$  for all  $t$  to obtain the normalized EPU time-series index. We use the same approach for the other EPU indices described below.

United States, Historical (1900-2014, monthly): We rely on archives for the LA Times, Chicago Tribune, Boston Globe, Wall Street Journal, NY Times and Washington Post from 1900 to 1984 and all ten papers listed above from 1985 to 2010. In constructing the historical US index, we expanded the economy term set to include “business”, “industry”, “commerce” and “commercial” in addition to “economy” and “economic”. We expanded the policy term set to include “war” and “tariff”, as discussed in Section 3.1. We splice the 6-paper and 10-paper series based on their overlap from 1985 to 1994 as follows: First, we adjust the 10-paper modern series multiplicatively to match the standard deviation of the historical series. Second, we additively adjust the modern series to match the level of the historical series during the overlap period.

United States (1985-, daily): We search archives for all daily-circulation US newspapers available through Access World News Newsbank service. The US daily EPU index uses the same term sets as the modern US monthly index.

Canada (1985-, monthly): We search the Gazette (from 1985), Globe and Mail (1985), Canadian Newswire (1999), Ottawa Citizen (1986), Toronto Star (1985), and Vancouver Sun (1987) using Proquest newspaper archives. The policy term set is spending, policy, deficit, budget, tax, regulation, and “central bank”.

China (1995-, monthly): We search the South China Morning Post using Proquest. In addition to meeting E, P and U requirements, an article must meet a “C” requirement to contribute to our EPU count: in particular, it must contain “China” or “Chinese”. To meet our P requirement for China, an article must satisfy the following text filter: {{policy OR spending OR budget OR political OR "interest rates" OR reform} AND {government OR Beijing OR authorities}} OR tax OR regulation OR regulatory OR "central bank" OR "People's Bank of China" OR PBOC OR deficit OR WTO. We use this compound filter, because it outperforms simpler alternatives in the audit study that we performed on 500 randomly selected articles that meet the E, U and C requirements.

France (1987-, monthly): We search Le Monde (from 1987) using Lexis Nexis and Le Figaro (from 2002) using Factiva. Our term sets are (E) *economie* OR *economique* OR *economiques*; (P) *taxe* OR *taxes* OR *impot* OR *impots* OR *politique* OR *politiques* OR *regulation* OR *regulations* OR *reglementation* OR *loi* OR “*lois reglementations*” OR *depense* OR *depenses* OR *deficit* OR *deficits* OR “*banque centrale*” OR “*BCE*” OR “*Reserve Federale*” OR *budget* OR *budgetaire*; and (U) *incertitude* OR *incertain* OR *incertitudes* OR *incertains*. To splice the two newspaper-level sources and construct the EPU index for France, we proceed as follows. First, we standardize the raw Le Monde EPU series to have unit standard deviation from 1987 to 2009 and normalize to 100 over the same period. Second, using the resulting standardized and normalized Le Monde EPU series, we compute its standard deviation and mean from 2002 to 2014. Third, we multiplicatively standardize the Le Figaro EPU series from 2002 to 2014 to match the standard deviation of the standardized/normalized Le Monde series from 2002 to 2014. Then we additively normalize the resulting Le Figaro series from 2002 to 2014 to match the mean of the standardized/normalized Le Monde series from 2002 to 2014. Finally, we use the standardized/normalized Le Monde EPU from 1987 to 2001 and the simple mean of the two standardized/normalized newspapers from 2002 onwards.

Germany (1993-, monthly): We search Handelsblatt and the Frankfurter Allgemeine Zeitung using each newspaper’s own archives. Our term sets are (E) *wirtschaft* OR *wirtschaftlich*; (P) *steuer* OR *wirtschaftspolitik* OR *regulierung* OR *regulierungs* OR *ausgaben* OR *bundesbank* OR *EZB* OR *zentralbank* OR *haushalt* OR *defizit* OR *haushaltsdefizit*; and (U) *unsicher* OR *Unsicherheit*.

India (2003-, monthly): We search the Economic Times (2003), Times of India (2003), Hindustan Times (2004), The Hindu (2003), Financial Express (2003), Indian Express (2003), and the Statesman (2003) using Access World News. All are English-language newspapers. The P term set, which we developed in conjunction with Sanjai Bhagat, Pulak Ghosh and Srinivasan Rangan, is *regulation*, *deficit*, *legislation*, *reform*, “*fiscal policy*”, “*monetary policy*”, “*central bank*”, “*RBI*”, “*Reserve Bank*”, *parliament*, “*finance ministry*”, *policymakers*, “*finance minister*”, *lawmakers*, “*planning commission*”, “*economic advisor*”, “*Prime Minister’s Office*”,

“PM Office”, “PMEAC”, “PMO”, “Lok Sabha”, tax, taxes, taxation, “excise duties”, and “customs duties”.

Italy (1997-, monthly): We search the Corriere Della Sera and La Repubblica using Factiva. Our term sets are (E) economia OR economico OR economica OR economici OR economiche; (P) tassa OR tasse OR politica OR regolamento OR regolamenti OR spesa OR spese OR spesa OR deficit OR "Banca Centrale" OR "Banca d'Italia" OR budget OR bilancio; and (U) incerto OR incerta OR incerti OR incerte OR incertezza.

Japan (1988-, monthly): We search Asahi and Yomiuri using each newspaper’s own archives. Leading Japanese newspapers routinely translate some of their articles into English, a practice that greatly facilitated our development of suitable Japanese-language E, P and U terms. We first identified Japanese newspaper articles translated into English that meet our EPU criteria. We (i.e., our Japanese research assistants) then reviewed the Japanese-language versions of the same articles to identify the Japanese terms that correspond to the English-language terms of interest. Using this approach, we developed the E, P and U term sets set forth in the following table:

Term Sets for Japan EPU Index, with Translations to English

Category	English	Japanese	In Chinese Characters
U	uncertainty OR uncertain	futoumei OR fukakujitsu	不透明 OR 不確実性
E	economic OR economy	Keizai	經濟
P	Policy Tax government spending  Regulation Bank of Japan OR BOJ budget Deficit Federal Reserve	Seisaku Zei saishutsu OR kokyo-jigyohi OR kokyotoushi OR kokuhi Kisei nihonginko OR nichigin Zaisei akaji OR fusai Renspou junbi OR rengin	政策 稅 歳出 公共事業費 公共投資 国費 規制 日本銀行 日銀 財政 赤字 負債

Russia (1992-, monthly): We search Kommersant’s own online archive from October 1992. We use Ekonomika (economy) for our E term set and “неопределённый” (uncertain) OR “неопределённость” (uncertainty) for our U term set. Our P term set is “politika” (policy), “nalog” (tax). For “spending”, there are several corresponding Russian words. For spending by the government, we consider a set of three terms: “rashody byudzheta” (budget outflows), “gosudarstvennye rashody” (government spending), and “rashodovanie” (spending). We translate “Regulation” as “regulirovanie”; Central Bank of Russia or CBR as “Centralnyj Bank Rossii” or “CBR”; and “Senate” as “Gosudarstvennaya Duma” (or “Gosduma” or “Duma”). The Russian counterpart to “White House” is “Kreml”. For “bill”, we use “zakon” or “zakonodatelnyj akt”, which is a synonym of “zakon” but used in more formal context. We translate “legislation” as “zakonodatelstvo”; “monetary policy” as “denezhnaya-kreditno politika”; trade policy as “torgovaya politika”; and “interest rate” as “procentnaya stavka”.

South Korea (1990-, monthly): We search Donga Ilbo, Kyunghyang, Maeil Economic (from 1995), Hankyoreh Hankook and Korea Economic Daily (from 1995) using the Mediagon archives. Our term sets are (E) economy OR economic OR commerce; (P) government OR “Blue House” OR congress OR authorities OR legislation OR tax OR regulation OR “Bank of Korea” OR “central bank” OR deficit OR WTO OR law/bill OR “ministry of finance”; and (U) uncertainty OR uncertain. To construct the South Korean EPU index, we first standardize each paper’s raw EPU rate to have unit standard deviation from 1995-2014. Using these standardized and normalized newspaper-level series, we average across papers by month to obtain the overall South Korean EPU index from January 1990 to December 2014.

Term Sets for South Korean EPU Index, with Translations to English

Category	English Terms	Korean Terms	In Korean Characters
U	uncertainty OR uncertain	bulhwaksilsung OR bulhwaksil	불확실성 OR 불확실
E	economic OR economy OR commerce	gyeongje OR gyeongjeui sangup or muyeok	경제 OR 경제의 상업 OR 무역
P	government “Blue House” congress authorities legislation  tax regulation  “Bank of Korea”  “central bank” deficit WTO  law/bill “ministry of finance”	jeongbu Chungwadae gukhoe dangguk jejeong OR jejeongbub OR ibbub  se gyuje OR tongje OR gyujeong  Hankukeunheng OR Haneun jungangeunheng jukja OR bujok WTO OR Segye muyeok gigu  bub OR buban gihwaekjaejungbu OR gijaebu	정부 청와대 국회 당국 제정 OR 제정법 OR 입법  세금 OR 세 규제 OR 통제 OR 규정  한국은행 OR 한은  중앙은행 적자 OR 부족 WTO OR 세계 무역 기구  법 OR 법안 기획재정부 OR 기재부

Spain (2001-, monthly): We search El Mundo and El Pais using Factiva. Our term sets are (E) económica OR economía; (P) impuesto OR tarifa OR regulacion OR politica OR gastar OR gasta OR gasto OR presupuesto OR deficit OR “banco central”; and (U) incierto OR incertidumbre.

United Kingdom (1997-, monthly): We search the Times of London and the Financial Times using the Access World News Newsbank service. Our term sets are (E) economic OR economy;

(P) spending OR policy OR deficit OR budget OR tax OR regulation OR “Bank of England”; and (U) uncertain OR uncertainty.

United Kingdom, Historical (1900-2010, monthly): We search the Times of London and the Guardian using the Proquest Historical Newspaper Archive. Our term sets are (E) economic OR economy OR business OR industry OR commerce OR commercial; (P) spending OR policy OR deficit OR budget OR tax OR regulation OR “Bank of England” or war or tariff; and (U) uncertain OR uncertainty.

### **B. Category-Specific Policy Term Sets (Figure 3 and Table 1)**

To create the category-specific EPU indices shown in Figure 3 and Table 1, we consider articles that contain our triple of terms about the economy, policy and uncertainty. We then check whether the article also contains one or more category-specific policy terms, as listed below.

- **Taxes:** taxes, tax, taxation, taxed
- **Government Spending & Other:** government spending, federal budget, budget battle, balanced budget, defense spending, military spending, entitlement spending, fiscal stimulus, budget deficit, federal debt, national debt, Gramm-Rudman, debt ceiling, fiscal footing, government deficits, balance the budget
- **Fiscal Policy:** Anything covered by **Taxes** or **Government Spending & Other**
- **Monetary Policy:** federal reserve, the fed, money supply, open market operations, quantitative easing, monetary policy, fed funds rate, overnight lending rate, the fed, Bernanke, Volker, Greenspan, central bank, interest rates, fed chairman, fed chair, lender of last resort, discount window, European Central Bank, ECB, Bank of England, Bank of Japan, BOJ, Bank of China, Bundesbank, Bank of France, Bank of Italy
- **Healthcare:** health care, Medicaid, Medicare, health insurance, malpractice tort reform, malpractice reform, prescription drugs, drug policy, food and drug administration, FDA, medical malpractice, prescription drug act, medical insurance reform, medical liability, part d, affordable care act, Obamacare
- **National Security:** national security, war, military conflict, terrorism, terror, 9/11, defense spending, military spending, police action, armed forces, base closure, military procurement, saber rattling, naval blockade, military embargo, no-fly zone, military invasion
- **Financial Regulation:** banking (or bank) supervision, glass-steagall, tarp, thrift supervision, dodd-frank, financial reform, commodity futures trading commission, cftc, house financial services committee, basel, capital requirement, Volcker rule, bank stress test, securities and exchange commission, sec, deposit insurance, fdic, fslic, ots, occ, firrea
- **Regulation:** Anything covered by **Financial Regulation** and truth in lending, union rights, card check, collective bargaining law, national labor relations board, nlr, minimum wage, living wage, right to work, closed shop, wages and hours, workers compensation, advance notice requirement, affirmative action, at-will employment, overtime requirements, trade adjustment assistance, davis-bacon, equal employment opportunity, eeo, osha, antitrust, competition policy, merger policy, monopoly, patent, copyright, federal trade commission, ftc, unfair business practice, cartel, competition law, price fixing, class action, healthcare lawsuit, tort reform, tort policy, punitive damages, medical malpractice, energy policy, energy tax, carbon tax, cap and trade, cap and tax, drilling restrictions, offshore drilling, pollution controls, environmental restrictions, clean air act, clean water act, environmental protection agency, epa, immigration policy



- **Sovereign Debt and Currency Crises:** sovereign debt, currency crisis, currency crash, currency devaluation, currency revaluation, currency manipulation, euro crisis, Eurozone crisis, european financial crisis, european debt, asian financial crisis, asian crisis, Russian financial crisis, Russian crisis, exchange rate
- **Entitlement Programs:** entitlement program, entitlement spending, government entitlements, social security, Medicaid, medicare, government welfare, welfare reform, unemployment insurance, unemployment benefits, food stamps, afdc, tanf, wic program, disability insurance, part d, oasdi, Supplemental Nutrition Assistance Program, Earned Income Tax Credit, EITC, head start program, public assistance, government subsidized housing
- **Trade Policy:** import tariffs, import duty, import barrier, government subsidies, government subsidy, wto, world trade organization, trade treaty, trade agreement, trade policy, trade act, doha round, uruguay round, gatt, dumping

### C. Constructing a Newspaper-Based Measure of Equity Market Uncertainty.

Our newspaper-based measure of policy uncertainty raises a basic question: Can frequency counts of newspaper articles serve to quantify economic uncertainty in a useful manner? To shed light on this question, we create a separate newspaper-based index of equity market uncertainty and compare it to the market-based VIX, a widely used measure of uncertainty in equity returns that is firmly grounded in option pricing theory.

To construct a newspaper-based measure of equity market uncertainty, we parallel the approach in Section 3.3 above. Specifically, we use the same newspapers, scaling methods and search criteria – except for dropping the policy-related term set and, instead, requiring an article to contain ‘stock price’, ‘equity price’ or ‘stock market’. Figure C2 plots the resulting newspaper-based index of equity market uncertainty and the monthly average of daily VIX values from 1990 to 2012. The two series are highly correlated. While the newspaper-based index is clearly noisier, it picks up every major move in the VIX during the sample period.

### D. Constructing Indicators Based on the FOMC Beige Books (Figure 7)

We reviewed all Beige Books from July 1983 to January 2015, covering more than 250 issues. For each instance of “uncertain\*” in the Beige Books, we read the surrounding passage to assess whether it refers to policy-related matters as a source of the uncertainty. If so, we treat the passage as being about policy uncertainty, at least in part. In these instances, we also classify the reference to policy uncertainty into one or more categories, similar to the ones in Table 1.

Outside the first few years, each Beige Book contains a statement along the lines of “Prepared ... based on information collected on or before” a specified date. This date is typically 7-12 days before the release date. For the early years, we imputed the specified date based on the average lag between the specified date and the release date in later years. Since Federal Reserve System staff gathers information over a period of time on or before the specified date, we subtract 14 days from the specified date to obtain an “effective” date for the information covered by each Beige Book. We assign Beige Books to calendar quarters using effective dates.

Given our uncertainty and policy uncertainty counts, we average over Beige Books within a calendar quarter to obtain our indicators. Figure C4 displays these raw counts. Figure 7 displays normalized counts that adjust for word count differences across Beige Books.

### E. Text Analysis of 10-K Filings to Quantify Policy Risk Exposure (Figure 7)

In 2005, the U.S. Securities and Exchange Commission (SEC) issued a regulation that requires most publicly held firms to include a separate discussion of “Risk Factors” in Part 1a of their annual 10-K filings. This discussion is intended to alert investors to risks specific to the company and industry. See Campbell et al. (2014) for an extended discussion and analysis.

Our text analysis of the Risk Factors section covers 10-K filings in calendar years 2006 to 2014 (fiscal years 2005 to 2013). The vast majority of 10-K filings occur in March, and most of the rest occur in February or April. We obtained machine-readable 10-K filings from the EDGAR database, using a Python script with the urllib2 package. We drop filings with an empty Risk Factors section. When a firm has more than one 10-K filing in the same calendar year, we retime the “early” (“late”) filing if the firm has no filing in the prior (next) calendar year.

For each 10-K filing, we count the number of sentences in the Risk Factors section that contains one or more of the following policy-relevant terms: government, political, legislative, legislation, congress, white house, regulation(s), regulatory, tax(es), fiscal polic(y/ies), monetary polic(y/ies), federal reserve, the fed, central bank, tariff(s), trade quota(s), antitrust, competition polic(y/ies), war(s), national security, government spending, defense spending, defense polic(y/ies), energy polic(y/ies), healthcare polic(y/ies), affordable care act, tort reform, import restriction(s), export restriction(s), investment restriction(s), patent polic(y/ies), patent law, trademark polic(y/ies), trademark law, copyright polic(y/ies), copyright law. Dividing this sentence count by the total number of sentences in the Risk Factors section yields our firm-year measure of exposure to policy-related risk factors. Averaging this ratio over firms by year yields the “Policy Share of 10-K Risk Factors” in Figure 7. Averaging over years for a given firm yields the 10-K policy risk exposure measure that we use in our firm-level panel regressions.

The following table reports data on the number of firms for which we obtained the Risk Factors section from 10-K filings on the Edgar Database. The second-to-last column shows the number of firm-level observations per year used in Figure 7. The last column shows the number of 10-K filings with a non-empty Risk Factors section that we match to Compustat using the CIK identifier. Our match rate ranges from 70 to 76 percent across years.

Filing Year	<i>Number of 10-Ks Identified</i>		<i>Number with Risk Factors Section Extracted</i>			
	All	Less Same-Date Duplicates	All	All Non- Empty	After Retiming	Matched to Compustat
2006	8852	8821	7161	5305	5319	4071
2007	8574	8524	6839	4995	4972	3770
2008	8746	8641	7154	5443	5443	4100
2009	9839	9785	7552	6242	6230	4356
2010	9165	9095	7442	6102	6109	4304
2011	8840	8750	8177	6731	6715	4751
2012	8393	8333	7908	6360	6369	4693
2013	8105	7998	7642	6096	6081	4597
2014	8084	7955	7591	6021	6049	4578

## F. Data on Federal Contracts and Government Healthcare Expenditures

We obtain data on federal contracts from 1999 to 2013 at USAspending.gov, a website mandated by the Federal Funding Accountability and Transparency Act of 2006. The site reports

individual federal contracts and includes information about the originating agency, contract recipient, contract amount, location of performance, and characteristics of the contract and recipient. We use information about the contract recipient and its parent company, if applicable, plus the date and contract amount. Unfortunately, most contract records do not include GV keys, stock tickers, or other unique firm identifiers that allow easy matching to external sources of data about the contract recipient. We match contracts to firms using DUNS numbers, when available; otherwise, we match on standardized names for contract recipients and parent firms.

To standardize firm names, we perform standard cleaning operations: removing punctuation and abbreviations, deleting excess spacing, replacing common misspellings, removing parentheticals, and other techniques to standardize firm names. We perform these operations on the universe of federal contract recipients and on the universe of ORBIS firms. We then match to ORBIS firm data by, in sequence, own DUNS number, parent DUNS number, own firm name, and parent firm name. Next, we use stock ticker data from ORBIS to match to quarterly Compustat data on publicly held firms. Using this procedure, we match about 45 percent of the contract awards and more than 65 percent of aggregate contract volume to Compustat firms. Imperfect matching accounts for a portion of the residual, but contract awards to independent privately held firms and public entities are the main reason we do not match all contract recipients. Public universities, states, and cities are some of the largest recipients of federal contract awards, and privately held firms account for a large share of private sector activity in the United States (Davis et al., 2007).

Using the matched dataset, we construct two sets of firm-level measures of federal contract intensity (hereafter, ‘intensity’) to provide cross-sectional variance in exposure to one aspect of policy uncertainty. The first is a measure at the three-digit SIC code level. Here we simply take the overall sum of contracts and sum of revenue by three-digit SIC code by year and take the ratio of the total contracts to total revenue, yielding an annual intensity measure. Finally, we take the average of these values by three-digit SIC code over time and apply the long-run average to that industry for all firms and years in the sample.

The second method uses firm segment data from Compustat in order to distribute both firm revenue and firm contracts to each of their component segments (defined by four-digit SIC codes). For instance, if one segment of a firm produces 50% of its revenue, we assign that segment 50% of contracts, as well. With this distribution completed, we sum contract dollars and revenue across four-digit SIC codes by year, obtaining four-digit SIC code level intensity measures, as in the three-digit SIC code approach. Using the four-digit SIC code intensities, we reconstruct a firm’s intensity based on its segment composition (so a firm with 50% of its revenue in one four-digit SIC code and 50% in another takes the simple average of the two SIC codes’ intensity levels). This approach yields firm-level variation in cross-sectional intensity of government contracting based on the four-digit SIC code makeup of each firm.

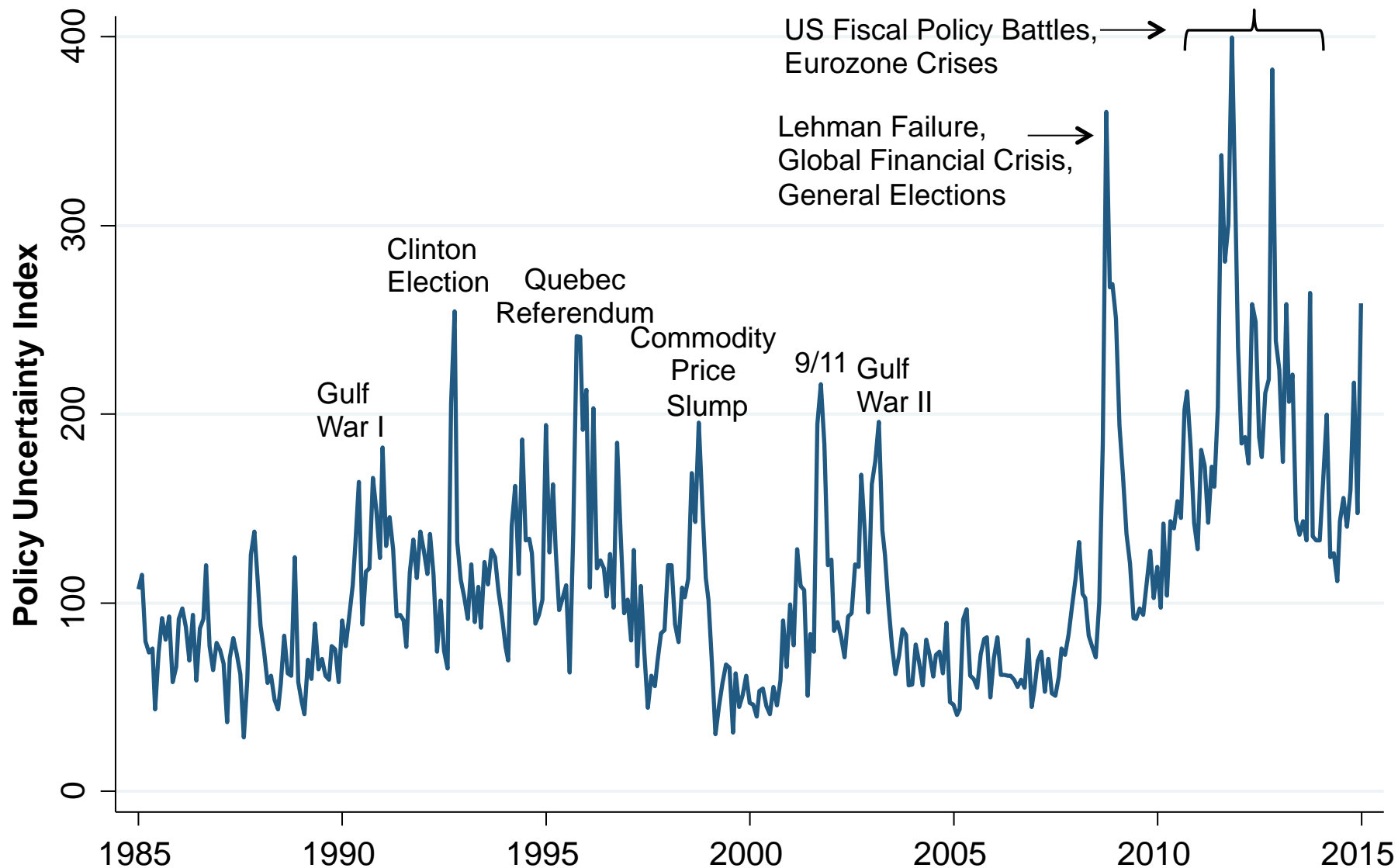
We obtain data on government and total national health expenditures for the United States from <http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/NHE2013.zip>. To obtain the government share, we sum health expenditures under Medicare, Medicaid, the Department of Defense, the Department of Veterans Affairs and the Children’s Health Insurance Program for 2010, then divide by total national health expenditures for 2010. This yields a value of 43.75 percent, which we assign to firms in SIC 800 (scaled by the firm’s share of revenues in SIC 800).

**Table A1: Effects on Firm-Level Implied Stock Price Volatility When Scaling EPU by its Components**

Dep Var: Log(30-day implied vol)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<b>Log(EPU)×Intensity</b>	0.215*** (0.069)						
<b>Log(EPU/E)×Intensity</b>		0.253*** (0.089)					
<b>Log(EPU/P)×Intensity</b>			0.206*** (0.069)				
<b>Log(EPU/U)×Intensity</b>				0.215** (0.104)			
<b>Log(EPU/EP)×Intensity</b>					0.223** (0.100)		
<b>Log(EPU/EU)×Intensity</b>						0.103 (0.175)	
<b>Log(EPU/PU)×Intensity</b>							0.262** (0.110)
<b>(Federal Purchases/GDP) ×Intensity</b>	-29.449** (12.723)	-26.932** (12.926)	-29.171** (12.742)	-28.825** (12.755)	-25.747** (13.090)	-24.629* (13.276)	-28.50** (13.00)
<b>F-test EPU coefficient=0.215</b>	n/a	0.673	0.902	0.998	0.936	0.524	0.669

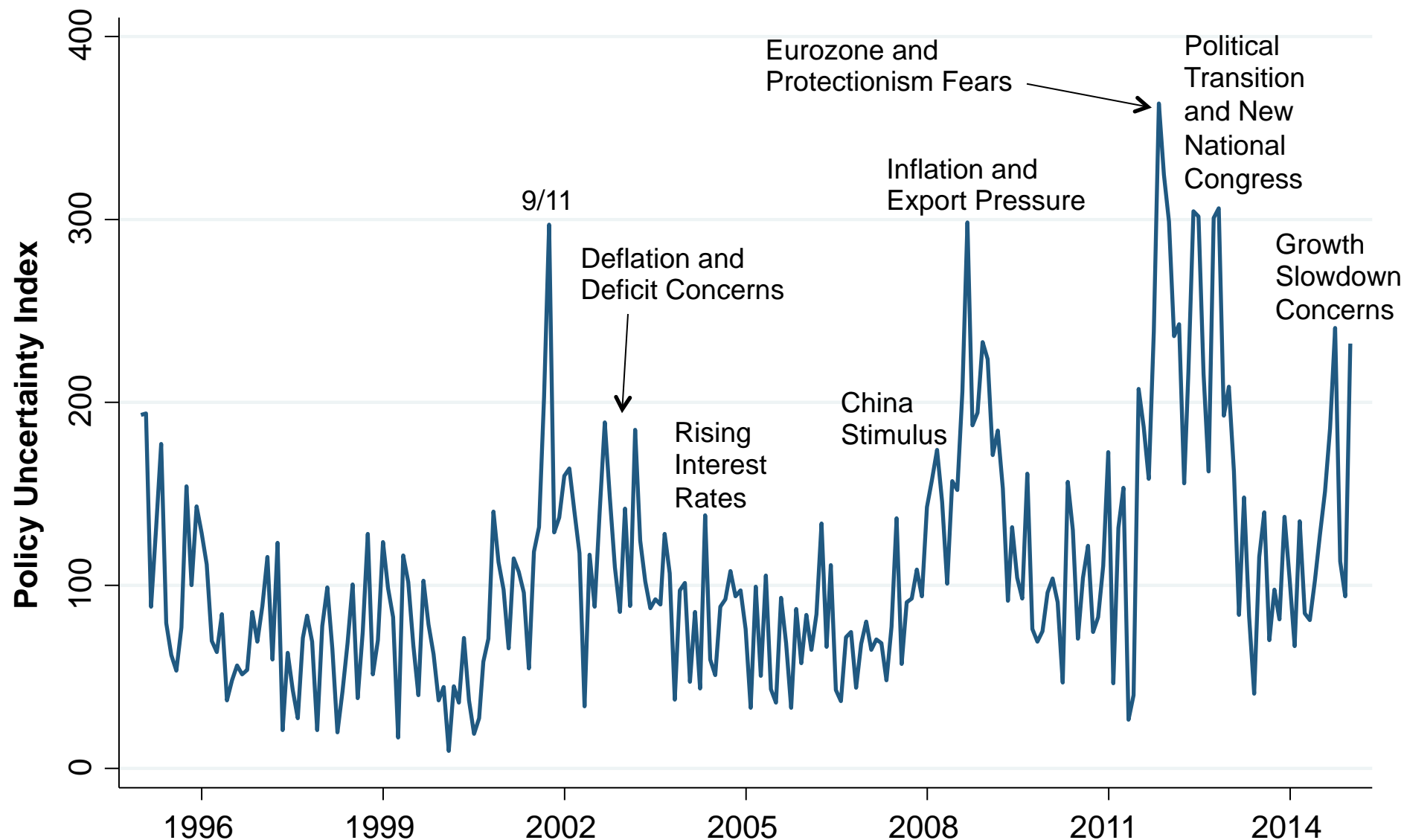
**Notes:** The sample contains 136,742 observations on 5,624 firms from 1996 to 2012. The dependent variable is the 30-day implied volatility for the firm, averaged over all days in the quarter. All regressions include a full set of firm and time fixed effects. **Log(EPU)×Intensity** is the log of the EPU index, multiplied by the firm’s exposure to federal government purchases of goods and services computed by the two-step method described in Section 4. **Log(EPU/E)×Intensity** is the same except that it scales the EPU index by the newspaper-based index for the frequency of articles that satisfy our E (“Economy”) criteria. Likewise, other rows consider analogs that scale the EPU index by newspaper-based indices that satisfy our P, U, EP, EU and PU criteria. **F-test EPU coefficient=0.215** tests whether the coefficient on the (scaled) EPU interaction is significantly different from the point estimate for the baseline regression in column (1). All regressions weighted by the firm’s average sales during the sample period. Standard errors based on clustering at the firm level.

**Figure A1: EPU Index for Canada, January 1985 to January 2015**



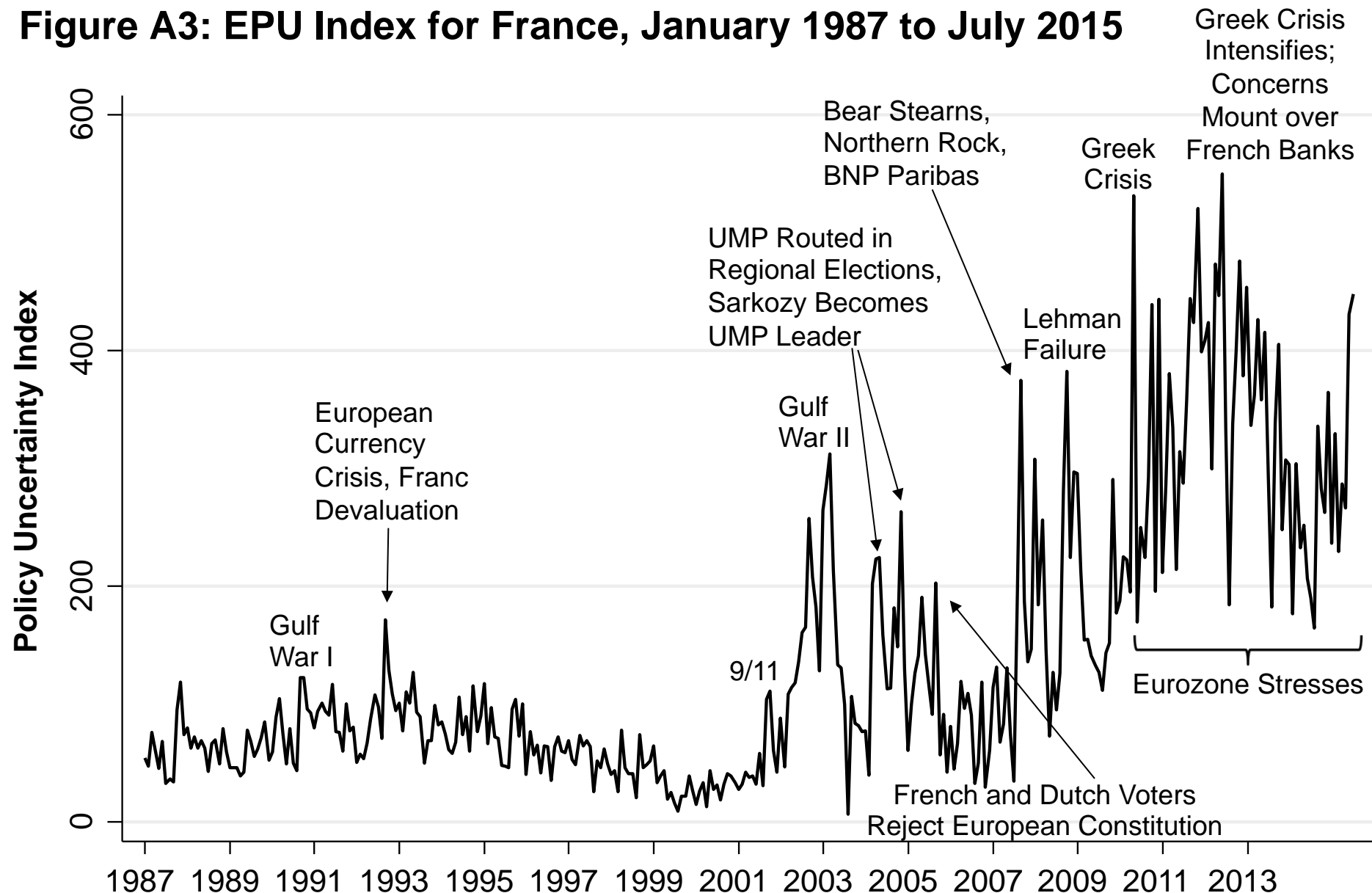
**Notes:** Index reflects scaled monthly counts of articles containing ‘uncertain’ or ‘uncertainty’, ‘economic’ or ‘economy’, and one or more policy-relevant terms: ‘tax’, ‘policy’, ‘regulation’, ‘spending’, ‘deficit’, ‘budget’, or ‘central bank’. The series is normalized to mean 100 from 1985 to 2010 and based on the following newspapers: The Gazette, The Globe and Mail, Canadian Newswire, the Ottawa Citizen, Toronto Star, and the Vancouver Sun.

**Figure A2: EPU Index for China, January 1995 to January 2015**



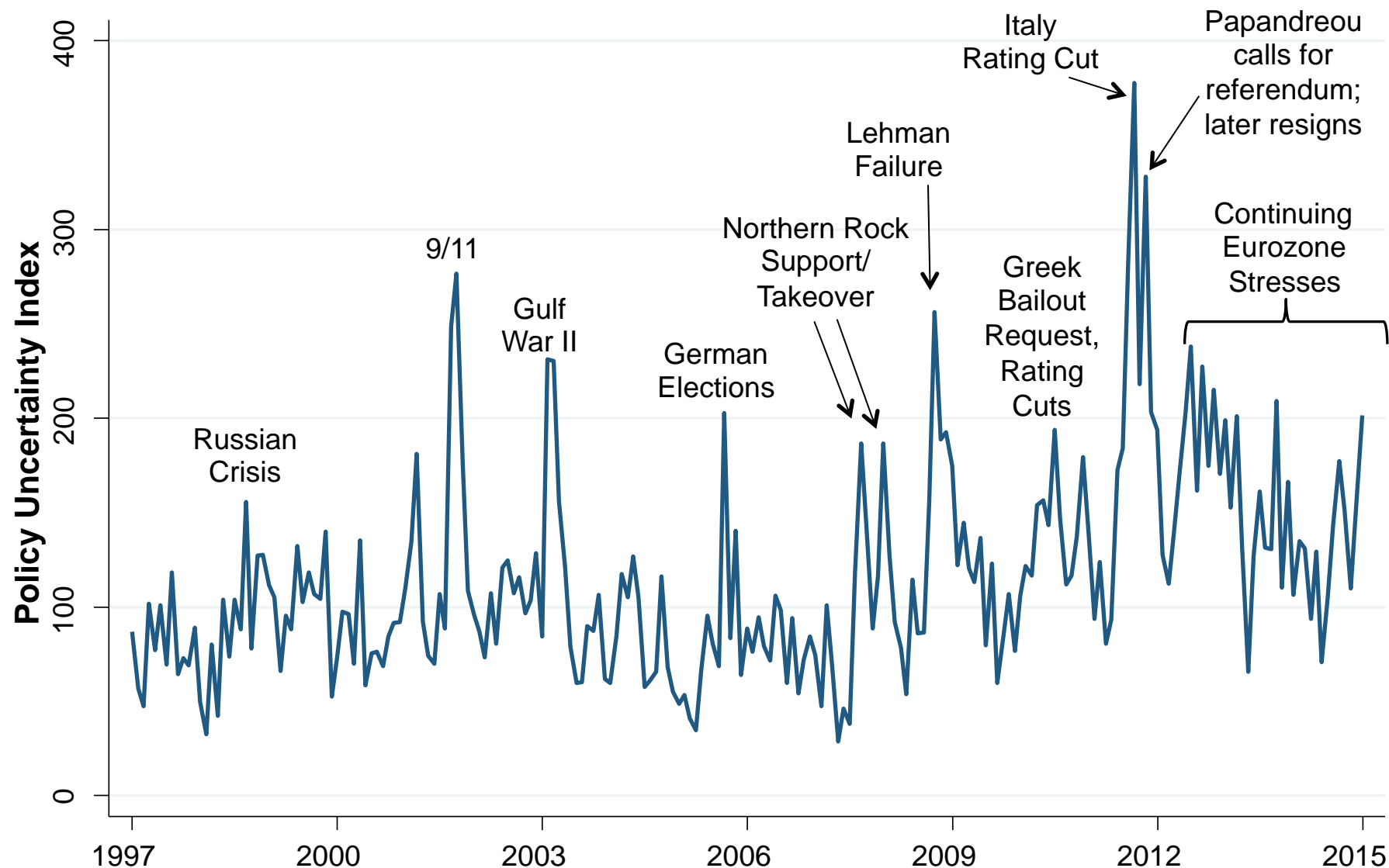
**Notes:** Index reflects scaled monthly counts of articles containing 'China' or 'Chinese', 'uncertain' or 'uncertainty', 'economic' or 'economy' and satisfying the 'policy' text filter specified for China in Appendix A. The series is normalized to mean 100 from 1985 to 2011 and based on the South China Morning Post, the leading English-language newspaper in Hong Kong.

**Figure A3: EPU Index for France, January 1987 to July 2015**



**Notes:** Index reflects scaled monthly counts of articles containing 'uncertain' or 'uncertainty', 'economic' or 'economy', and one or more policy-relevant terms: 'tax', 'policy', 'regulation', 'spending', 'deficit', 'budget', or 'central bank'. The series is normalized to mean 100 from 1997 to 2009 and based on the following newspapers: Le Monde and Le Figaro.

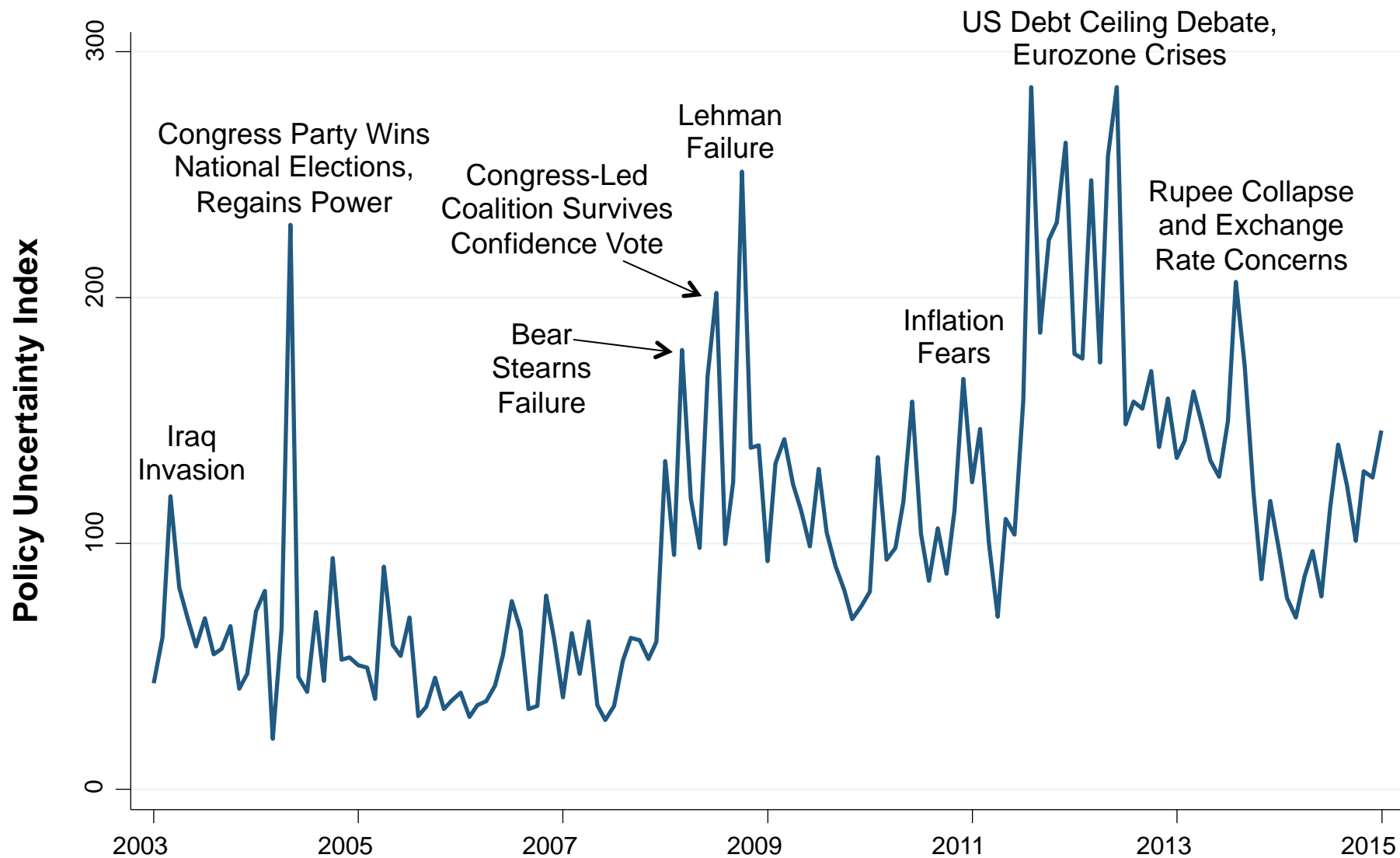
**Figure A4: EPU Index for Germany, January 1997 to January 2015**



**Notes:** Index reflects scaled monthly counts of articles containing ‘uncertain’ or ‘uncertainty’, ‘economic’ or ‘economy’, and one or more policy-relevant terms: ‘tax’, ‘policy’, ‘regulation’, ‘spending’, ‘deficit’, ‘budget’, or ‘central bank’. The series is normalized to mean 100 from 1997 to 2009 and based on the following newspapers: Frankfurter Allgemeine Zeitung and Handelsblatt.

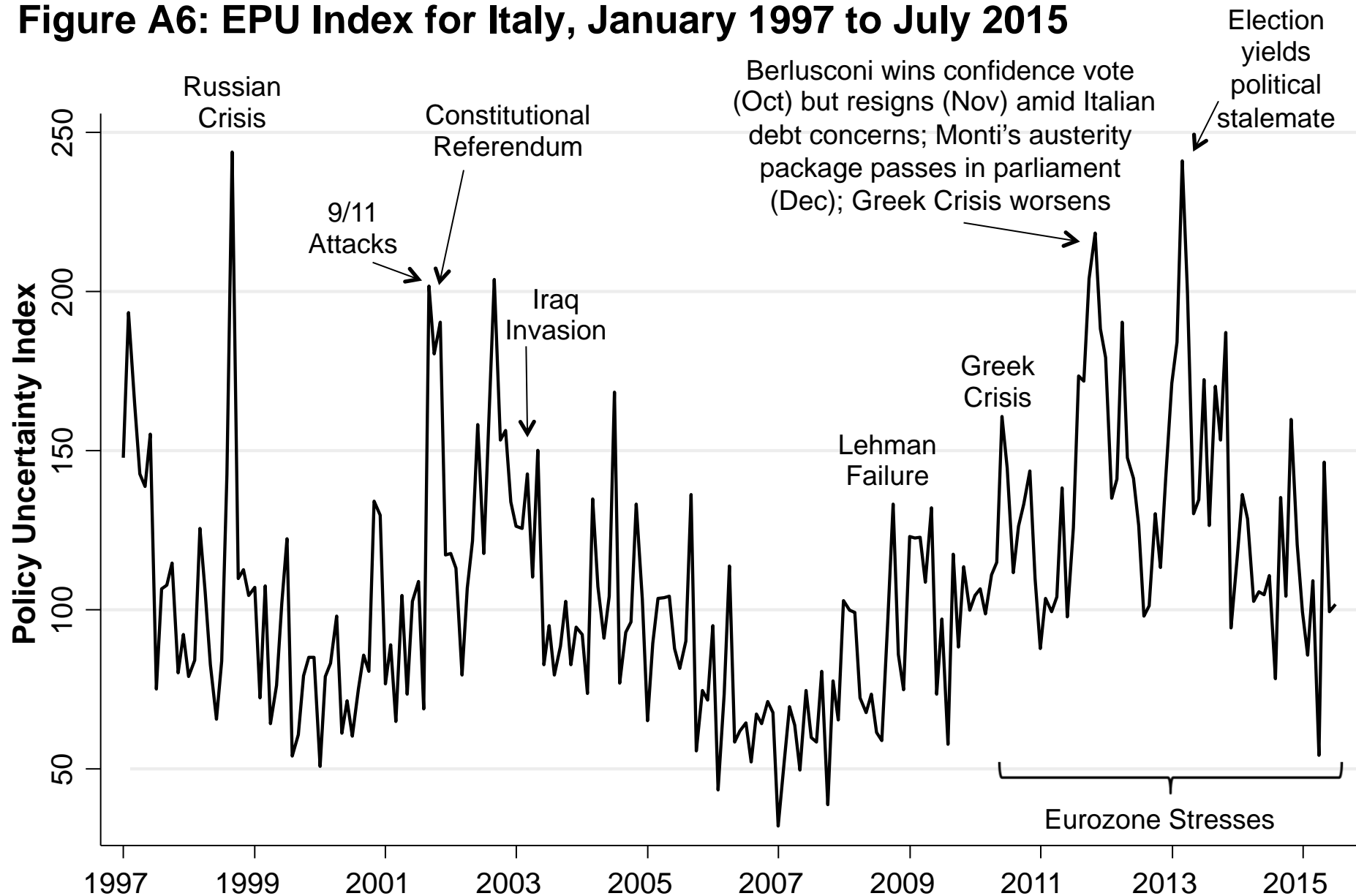


**Figure A5: EPU Index for India, January 2003 to January 2015**



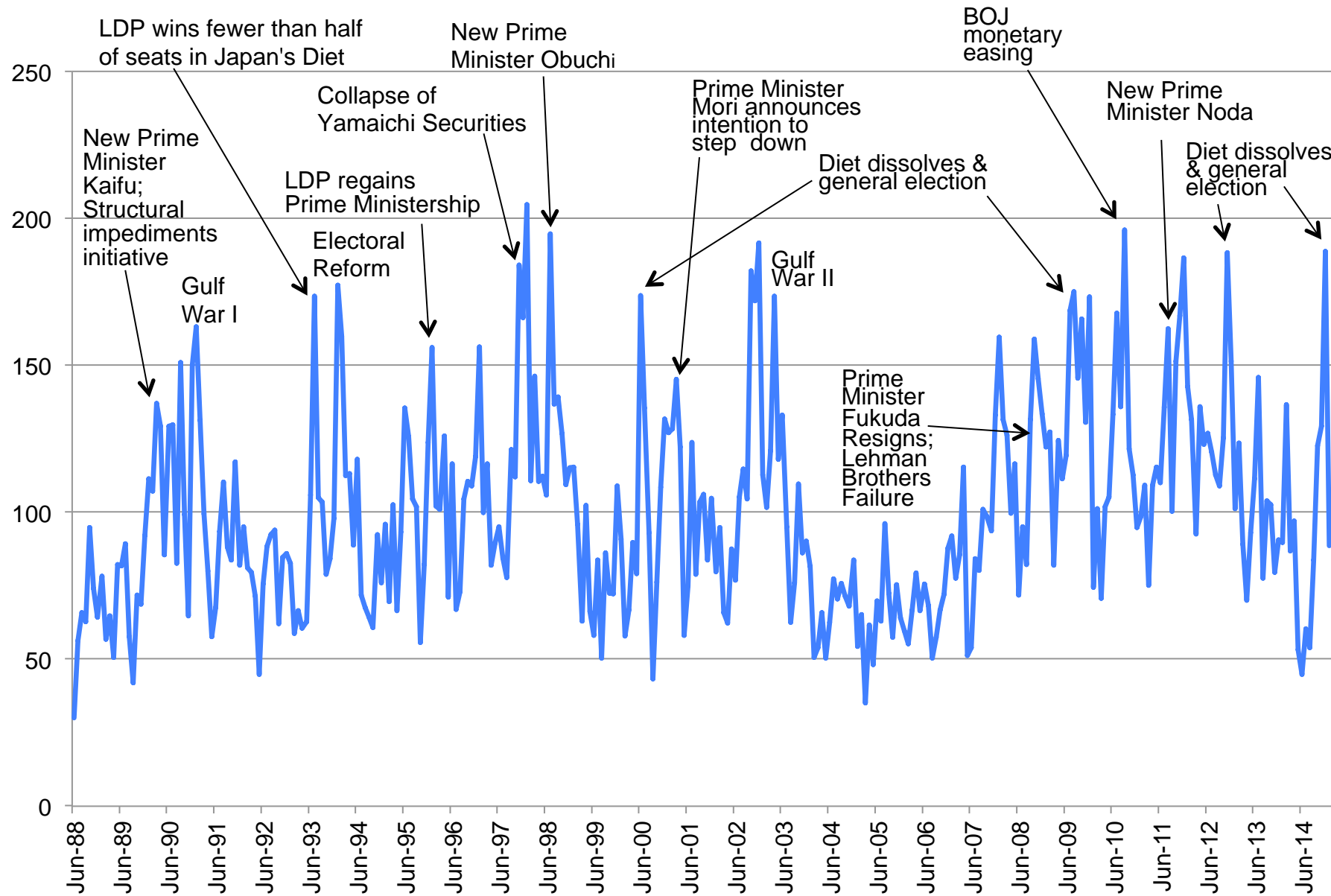
**Notes:** Index reflects scaled monthly counts of articles containing ‘uncertain’ or ‘uncertainty’ or ‘uncertainties’ or ‘uncertainties’, ‘economic’ or ‘economy’, and one or more of policy-relevant terms listed for India in Appendix A. The series is normalized to mean 100 from 2003 to 2010 and based on the following newspapers: The Economic Times, Times of India, Hindustan Times, The Hindu, Financial Express, Indian Express, and the Statesman.

**Figure A6: EPU Index for Italy, January 1997 to July 2015**



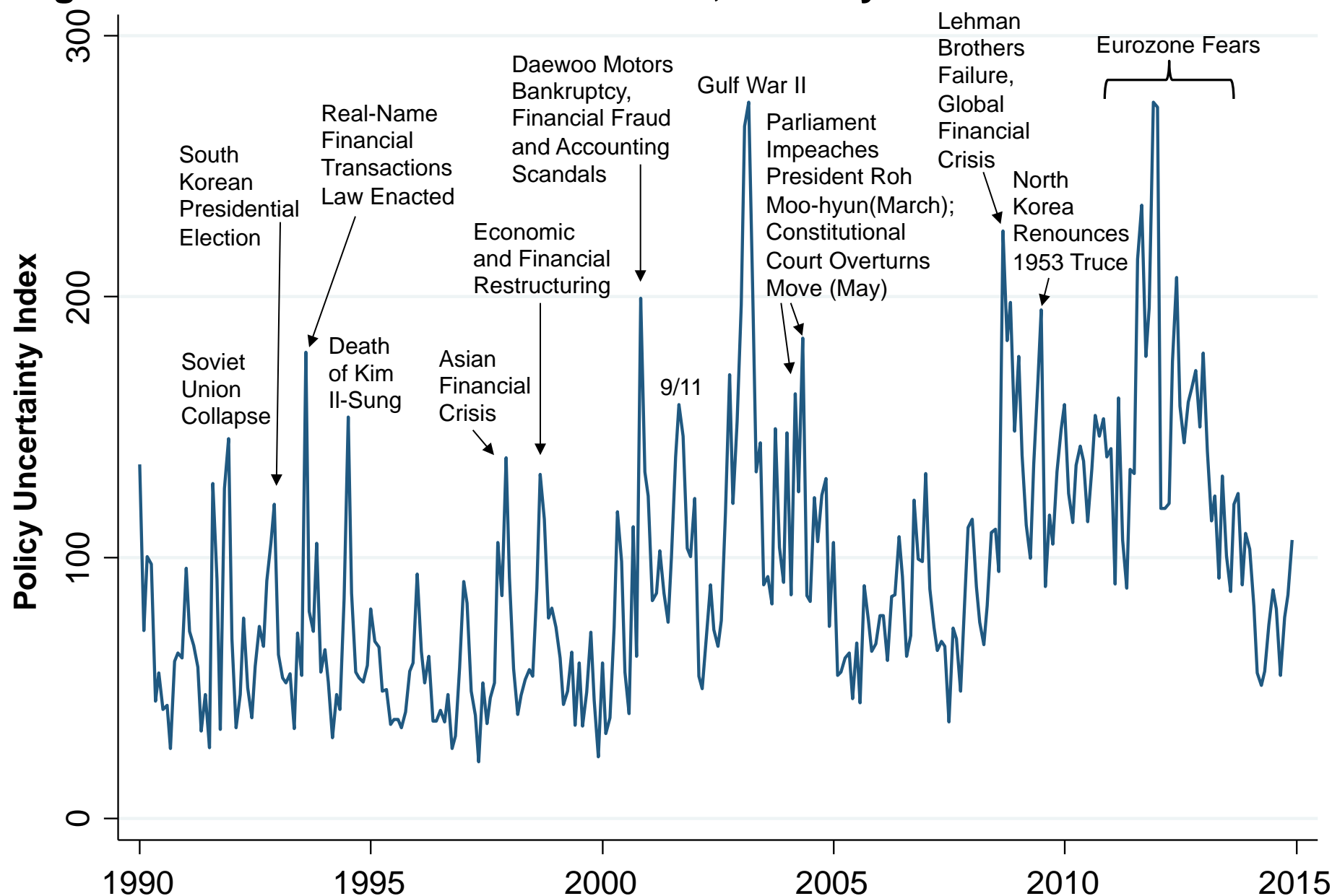
**Notes:** Index reflects scaled monthly counts of articles containing ‘uncertain’ or ‘uncertainty’, ‘economic’ or ‘economy’, and one or more policy-relevant terms: ‘tax’, ‘policy’, ‘regulation’, ‘spending’, ‘deficit’, ‘budget’, or ‘central bank’. The series is normalized to mean 100 from 1997 to 2009 and based on the following newspapers: La Stampa and Corriere Della Sera.

Figure A7: Index of Economic Policy Uncertainty for Japan



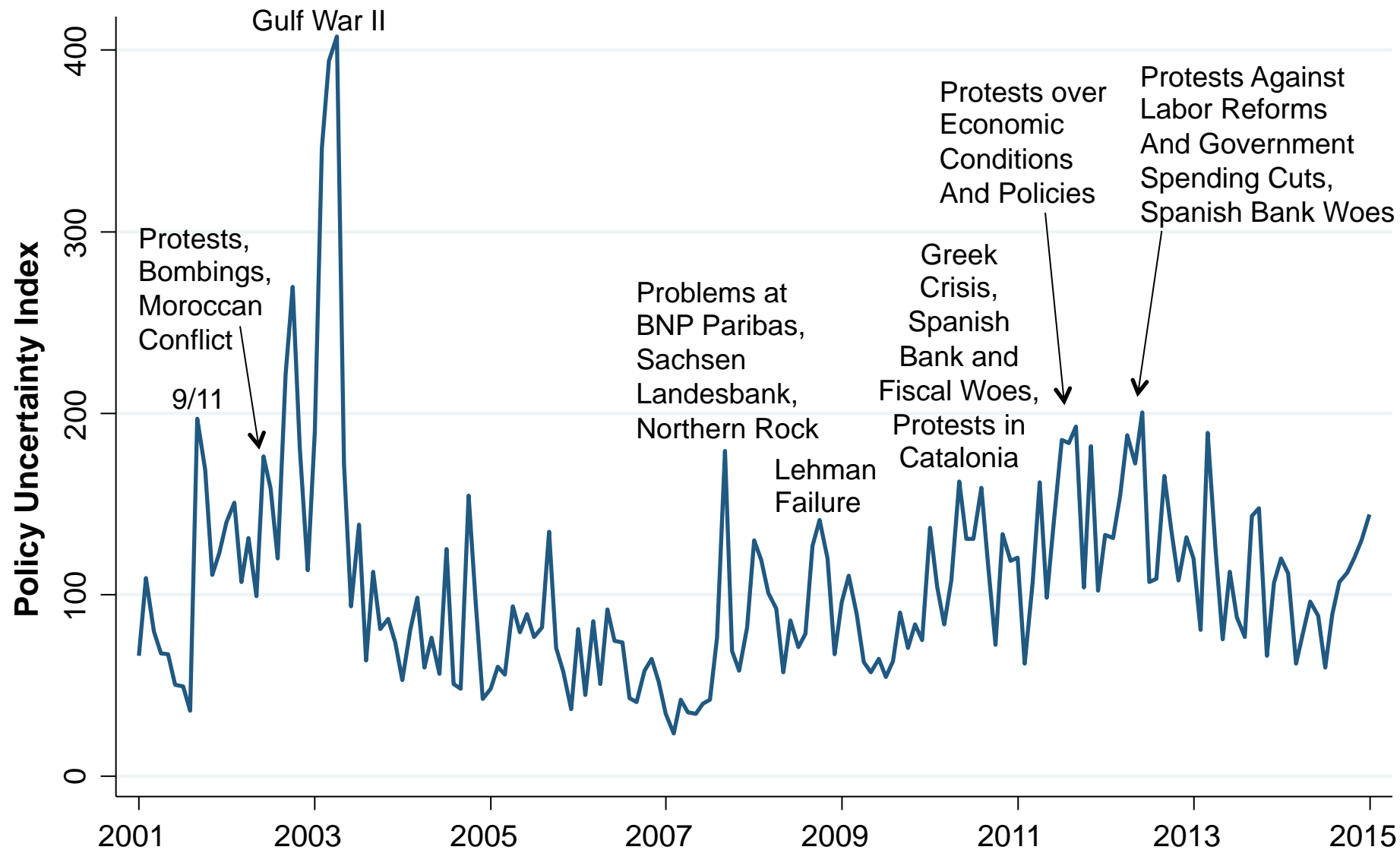
**Notes:** Index reflects scaled monthly counts of articles in Yomiuri and Asahi containing Japanese-language terms for 'uncertain' or 'uncertainty', 'economic' or 'economy', and one or more selected policy terms. The series is normalized to mean 100 from 1985-2009 and runs from June 1988 to January 2015.

# Figure A8: EPU Index for South Korea, January 1995 to December 2014



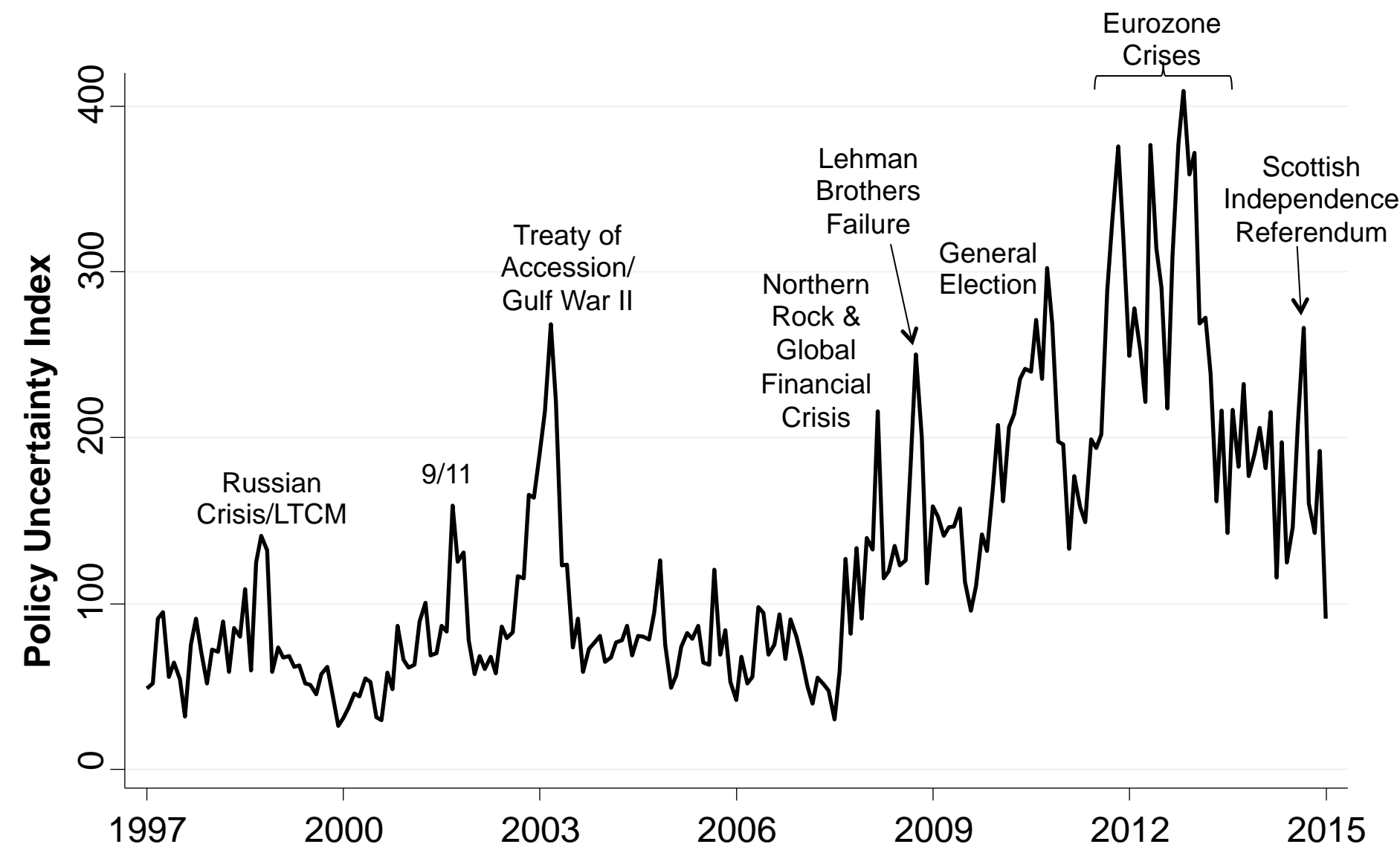
**Notes:** Index reflects scaled monthly counts of articles in six South Korean newspapers containing ‘uncertain’ or ‘uncertainty’, ‘economic’ or ‘economy’ or ‘commerce’, and one or more of the policy terms specified for South Korea in Appendix A. The series is normalized to mean 100 from 1995 to 2014.

**Figure A9: EPU Index for Spain, January 2001 to January 2015**



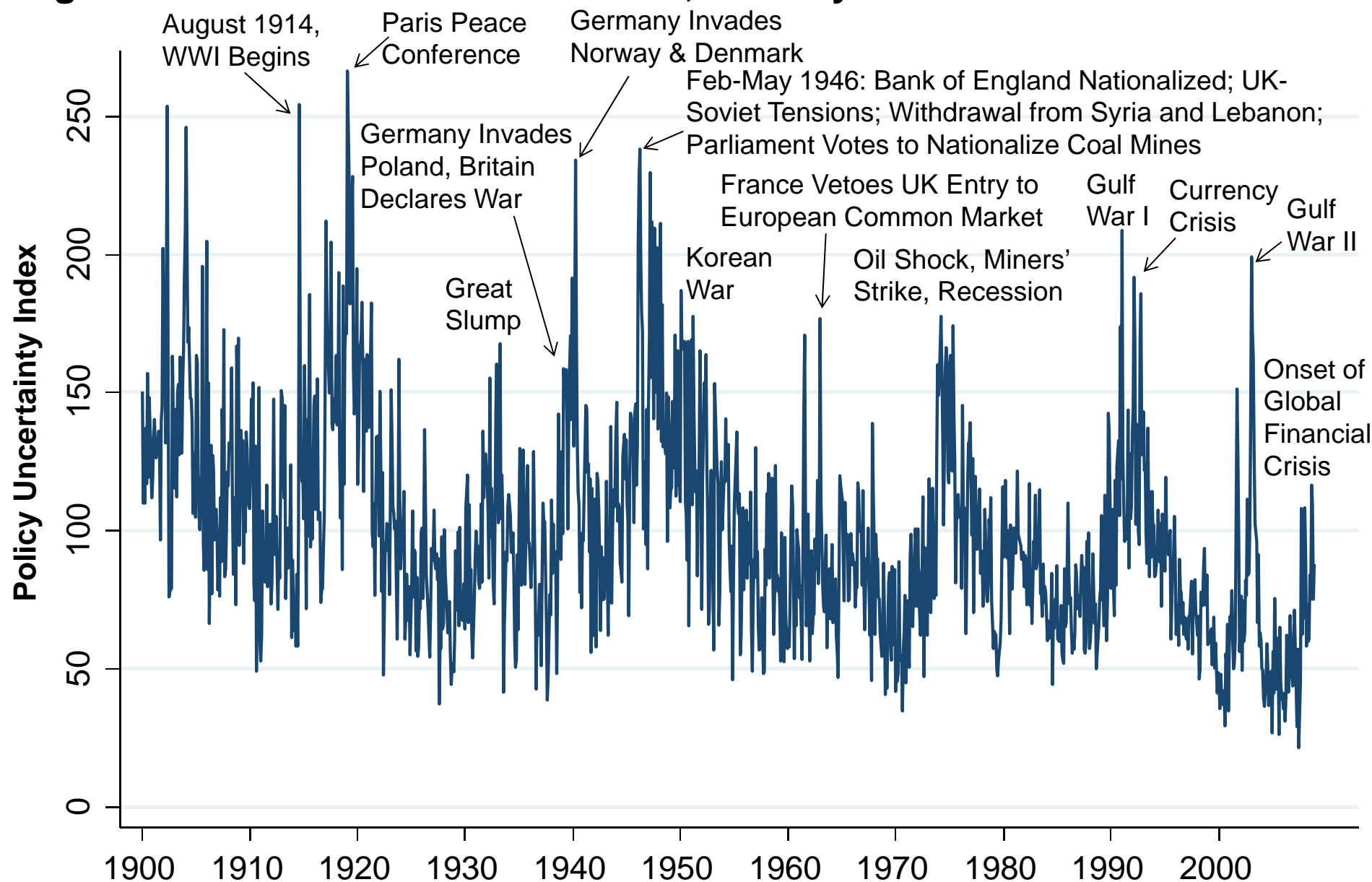
**Notes:** Index reflects scaled monthly counts of articles containing 'uncertain' or 'uncertainty', 'economic' or 'economy', and one or more policy-relevant terms: 'tax', 'policy', 'regulation', 'spending', 'deficit', 'budget', or 'central bank'. The series is normalized to mean 100 from 2001 to 2009 and based on queries in the following newspapers: El Pais and El Mundo

Figure A10: EPU Index for the United Kingdom, January 2001 to January 2015



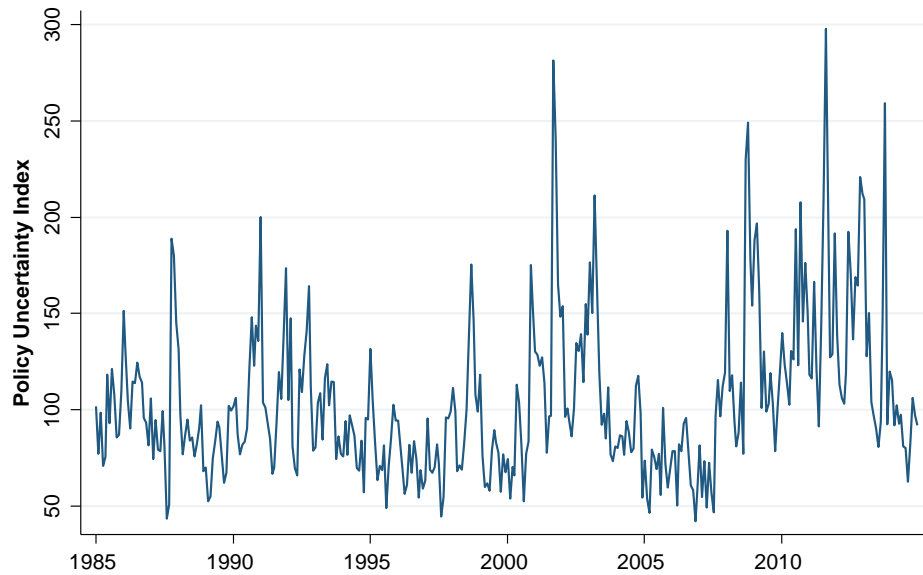
**Notes:** The news-based EPU Index reflects scaled monthly counts of articles containing ‘uncertain’ or ‘uncertainty’, ‘economic’ or ‘economy’, and one or more policy-relevant terms: ‘tax’, ‘policy’, ‘regulation’, ‘spending’, ‘deficit’, ‘budget’, or ‘central bank’. The series is normalized to mean 100 from 1997 to 2009 and based on queries in the following newspapers: The Times of London and the Financial Times.

**Figure A11: UK Historical EPU Index, January 1900 to December 2008**



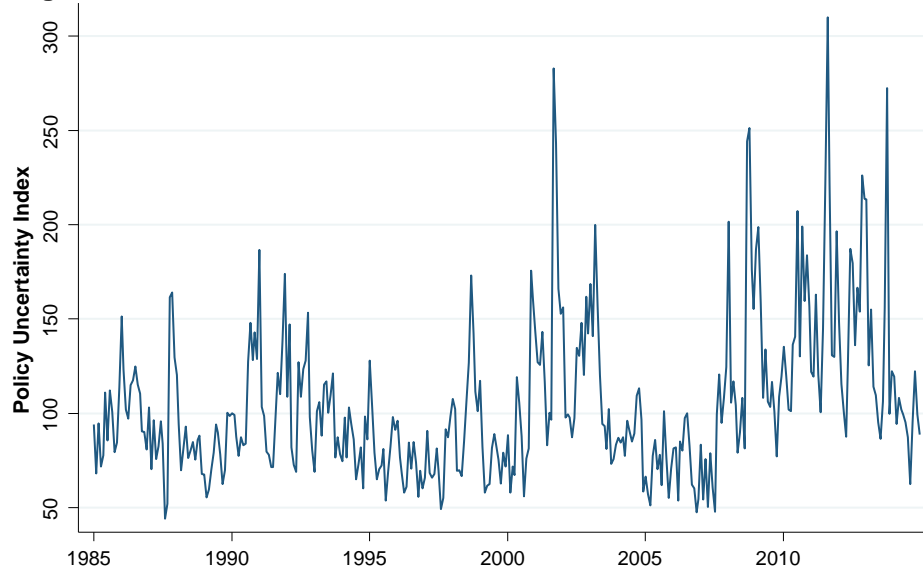
**Notes:** Index reflects scaled monthly counts of articles containing 'uncertain' or 'uncertainty'; 'economic', 'economy', 'business', 'industry', 'commerce', or commercial; and one or more of 'tax', 'policy', 'regulation', 'spending', 'deficit', 'budget', 'Bank of England', 'war', or 'tariff'. The series is normalized to mean 100 from 1900 to 2008 and based on The Times of London and The Guardian.

**Figure B1: The US EPU Index without ‘regulation’**



**Notes:** We construct this version of the US EPU index in the same manner as Figure 1, except for dropping ‘regulation’ (and ‘regulations’ and ‘regulatory’) from the policy term set.

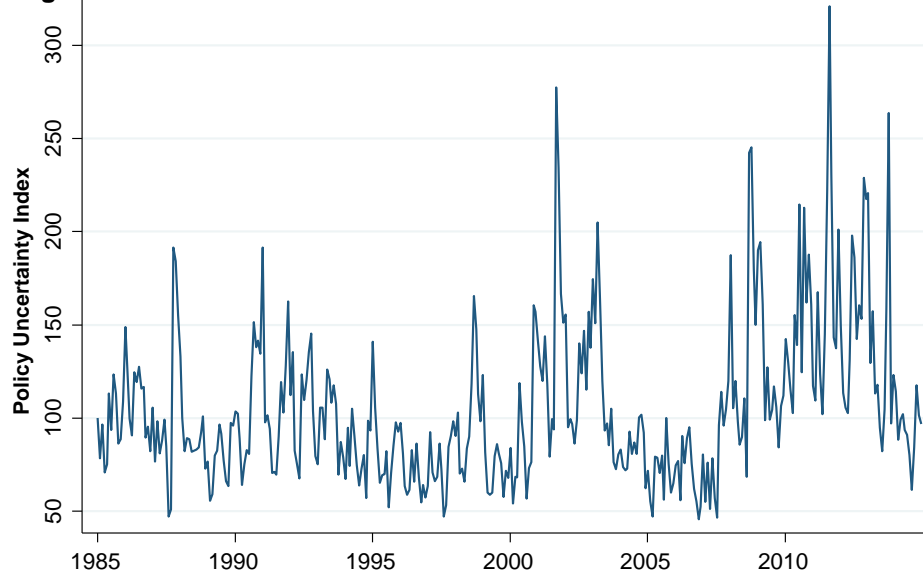
**Figure B2: US EPU Index without ‘deficit’**



**Notes:** We construct this version of the US EPU index in the same manner as Figure 1, except for dropping ‘deficit’ (and ‘deficits’) from the policy term set.

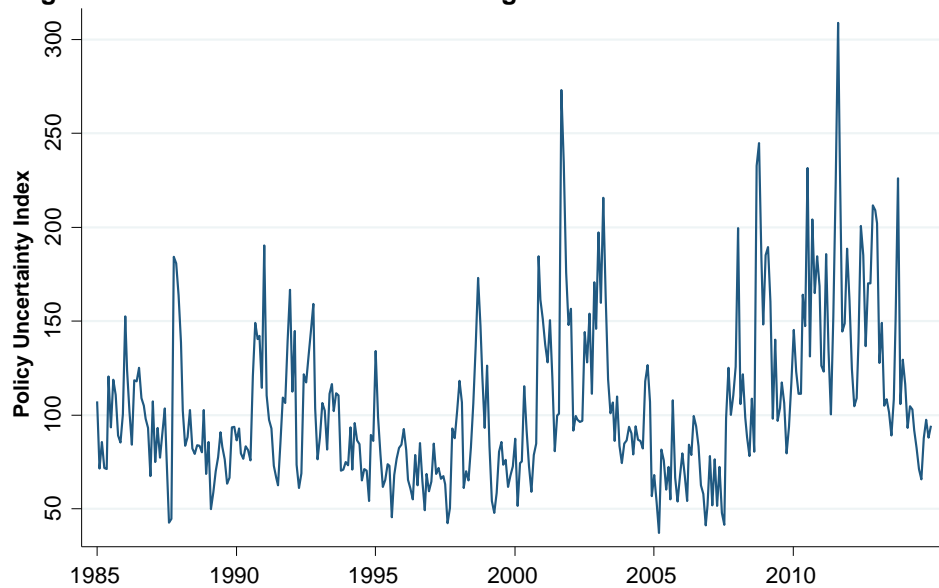


**Figure B3: US EPU Index without 'white house'**



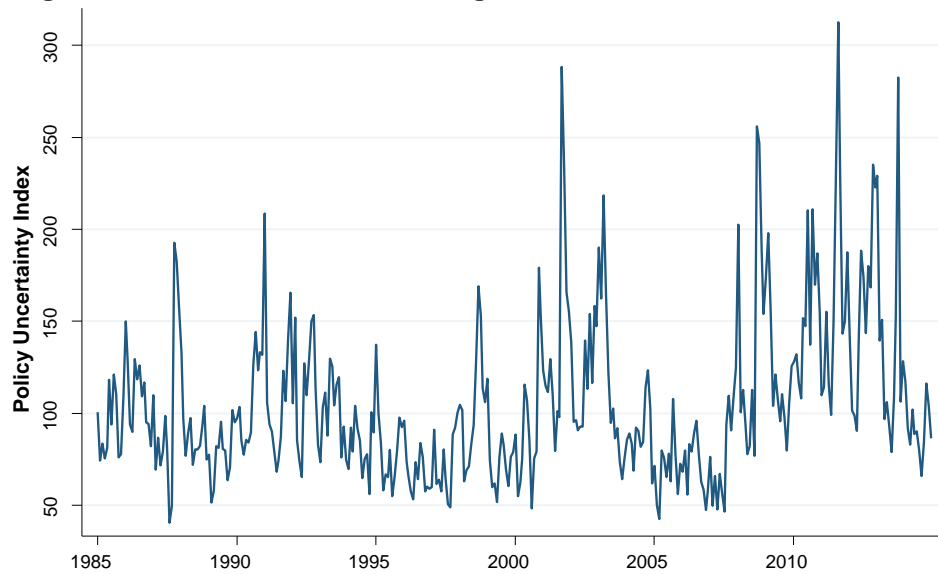
**Notes:** We construct this version of the US EPU index in the same manner as Figure 1, except for dropping 'white house' from the policy term set.

**Figure B4: US EPU Index without 'Congress'**



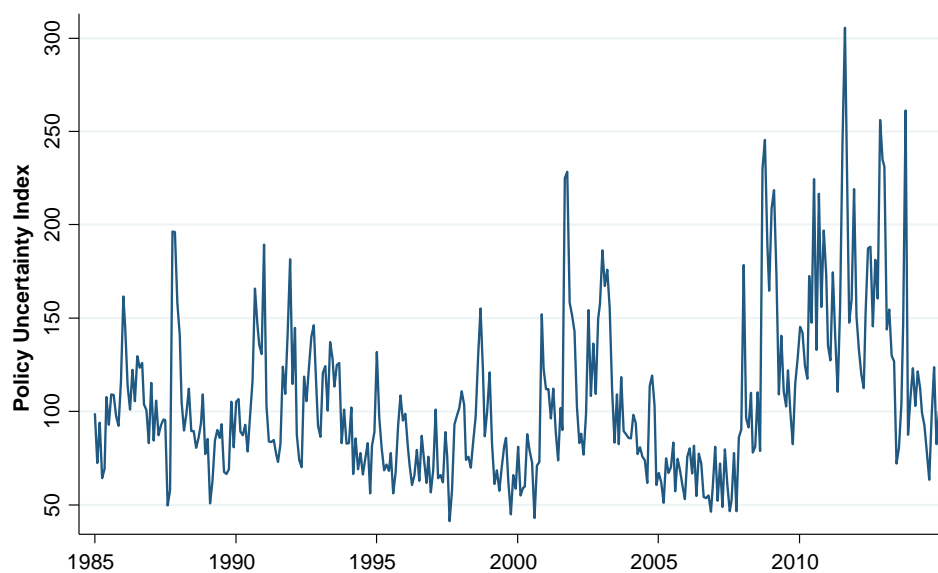
**Notes:** We construct this version of the US EPU index in the same manner as Figure 1, except for dropping 'Congress' (and 'Congressional') from the policy term set.

**Figure B5: US EPU Index without 'legislation'**



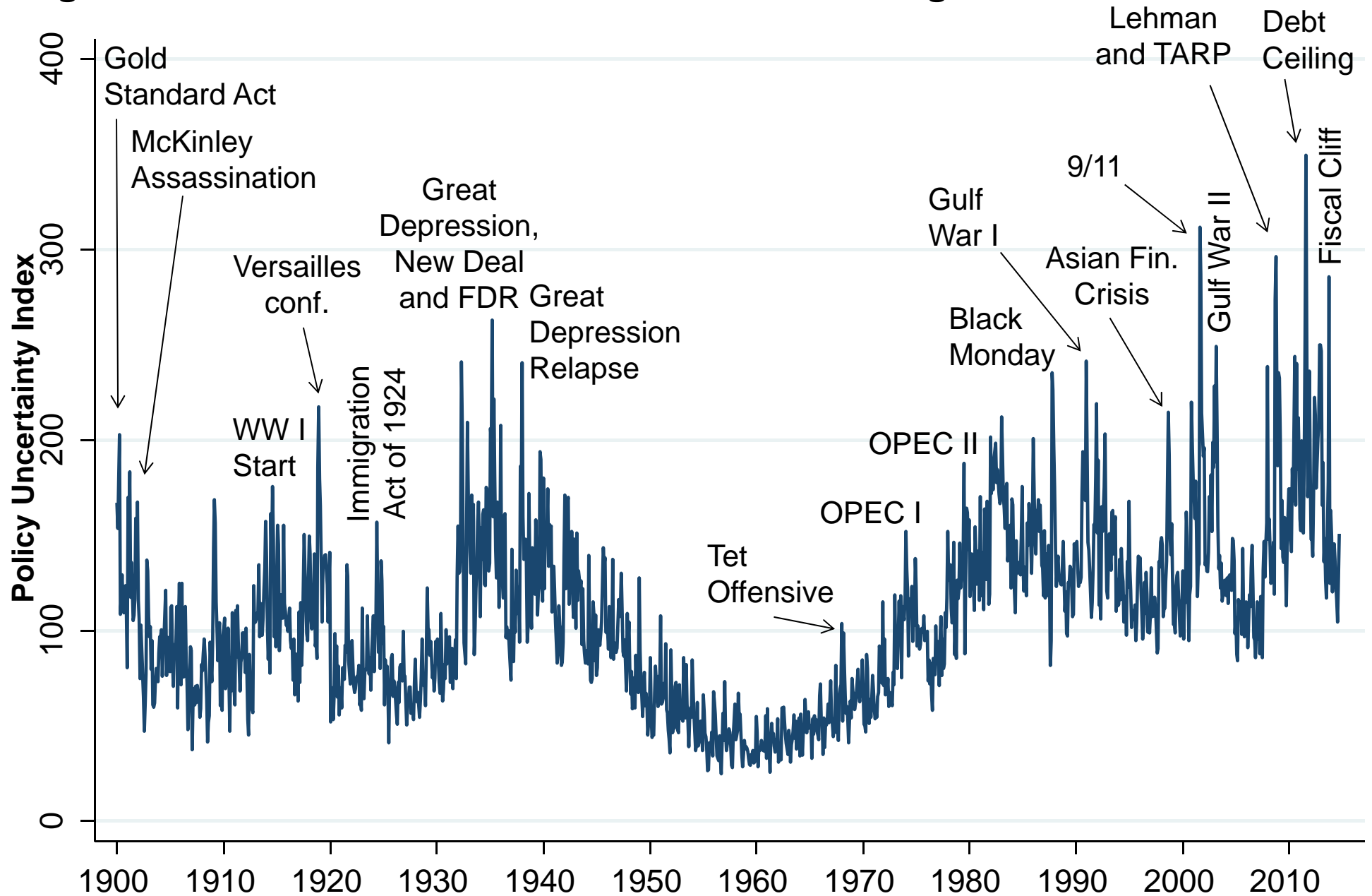
**Notes:** We construct this version of the US EPU index in the same manner as Figure 1, except for dropping 'legislation' (and 'legislative' and 'legislature') from the policy term set.

**Figure B6: US EPU Index without 'Federal Reserve'**



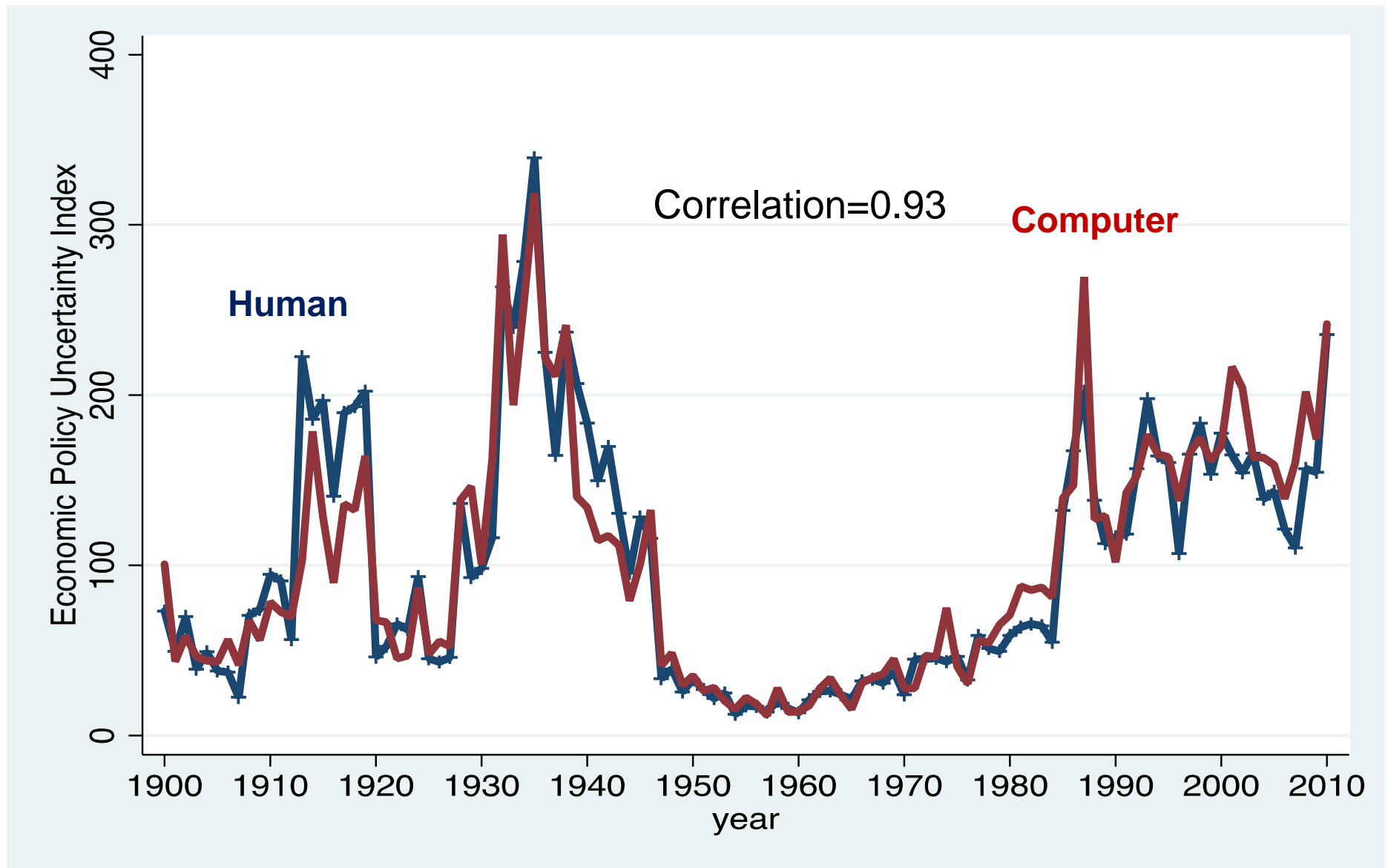
**Notes:** We construct this version of the US EPU index in the same manner as Figure 1, except for dropping 'Federal Reserve' (and 'the Fed') from the policy term set.

**Figure B7: Historical Index of US EPU – ‘All’ Scaling**



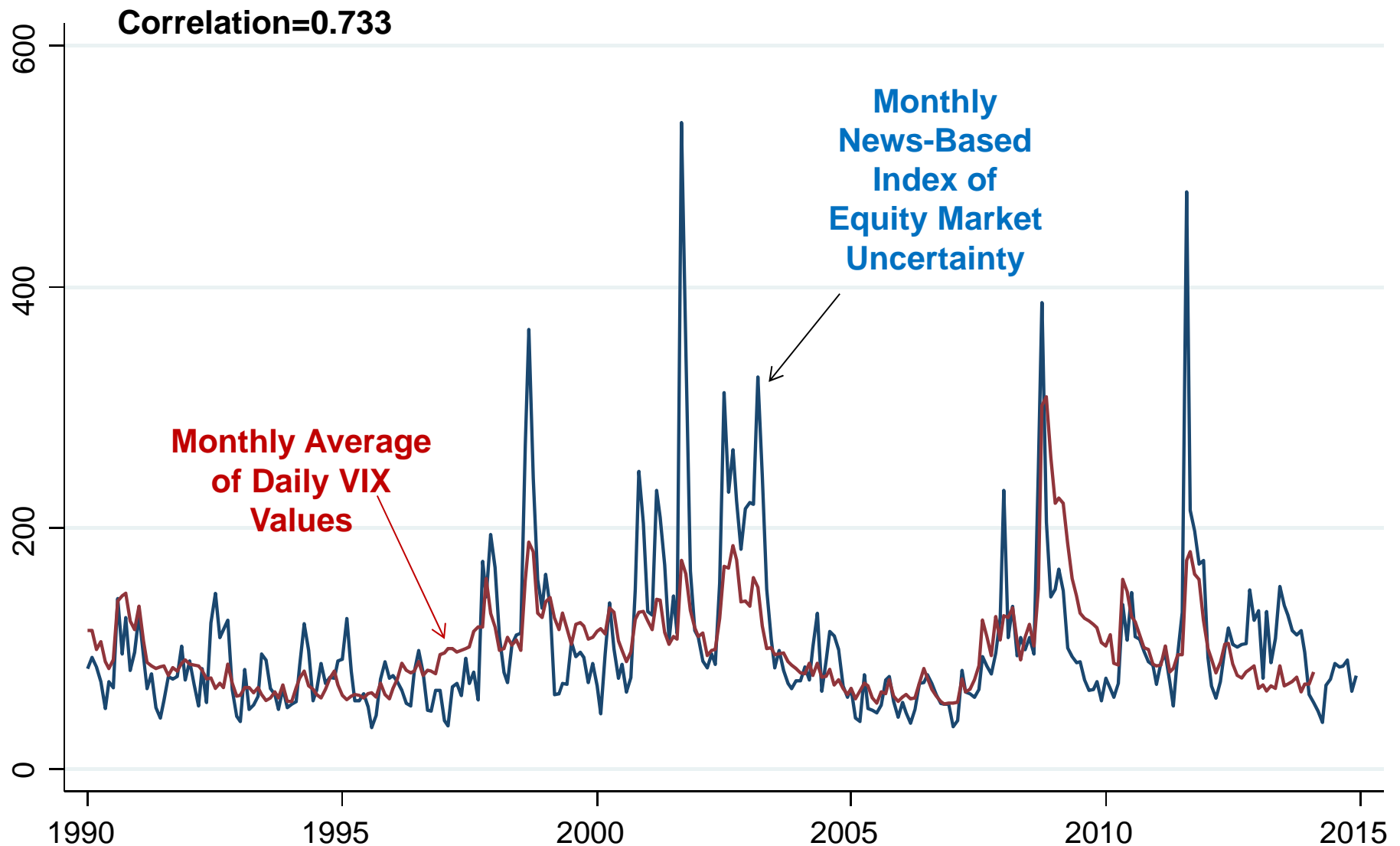
**Notes:** We construct this version of the US Historical EPU Index in the same manner as Figure 2, except we scale the raw newspaper-level EPU counts by the count of all articles in the same paper and month. In contrast, Figure 2 scales the raw EPU counts by the count of all articles in the same paper or month that contain one of the “economy” terms.

**Figure C1: Human and Computer EPU Indices, 1900-2010, Annual**



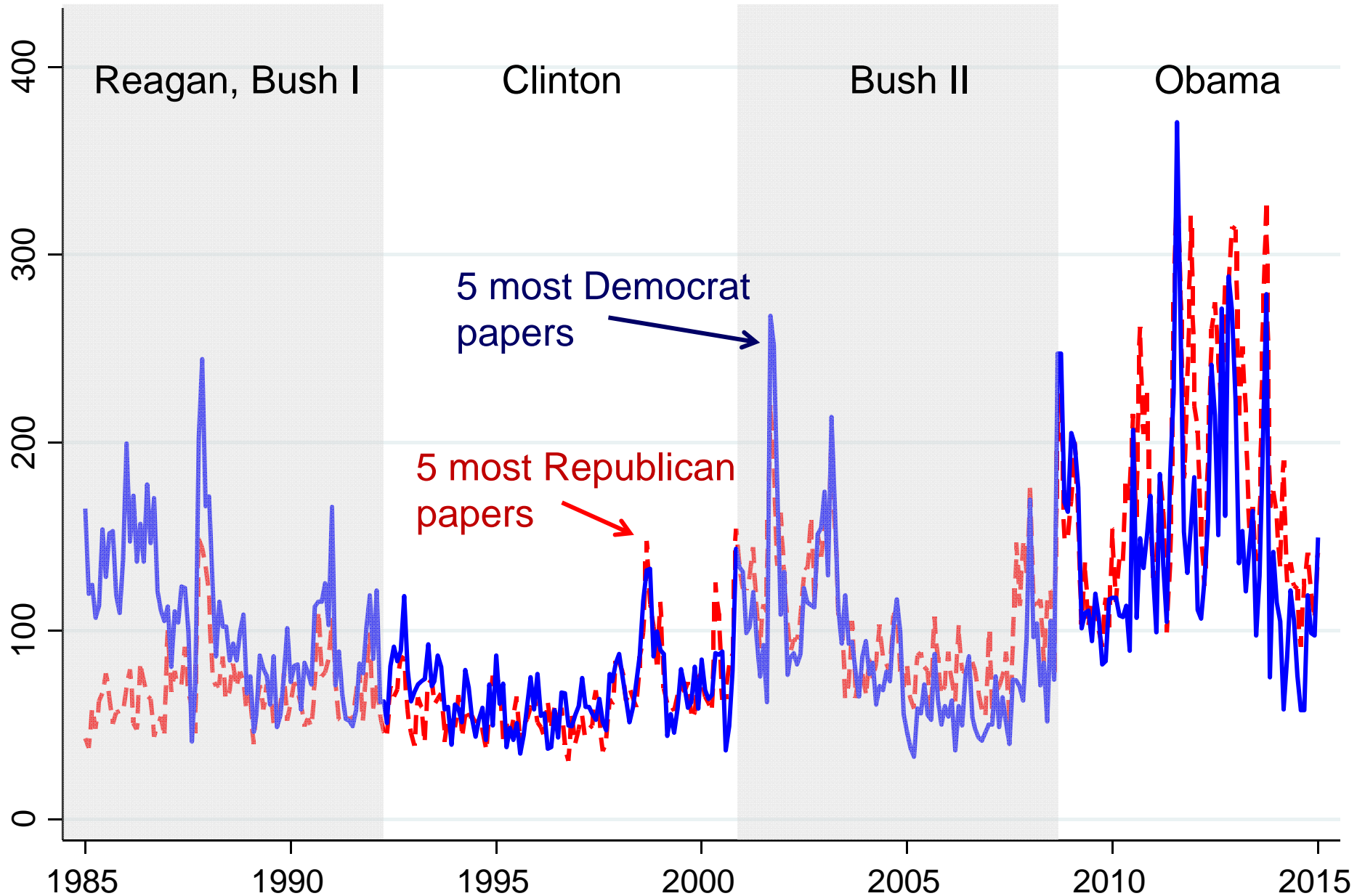
**Notes:** Index comparison from 1900 to 2010 based on 11,841 articles (15,156 audits) in the Chicago Tribune, Dallas Morning News, LA Times, Miami Herald, NY Times, San Francisco Chronicle, Washington Post and Wall Street Journal. Series plotted yearly to reduce sampling variability, with an average of 107 articles per year. Each series normalized to 100 from 1900 to 2010.

**Figure C2: News-based index of equity market uncertainty compared to market-based VIX, January 1990 to December 2014**



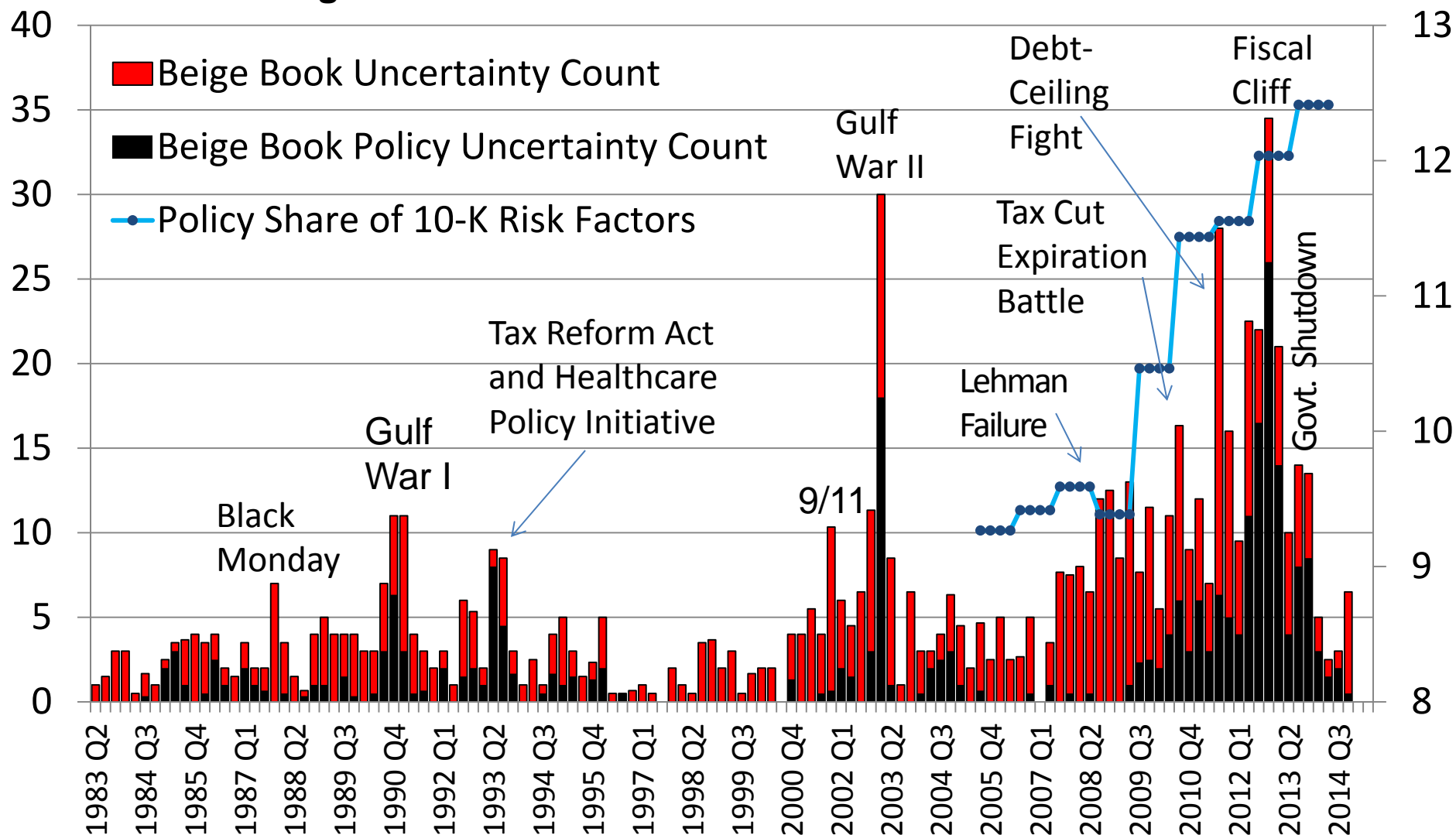
**Notes:** The news-based index of equity market uncertainty is based on the count of articles that reference 'economy' or 'economic', and 'uncertain' or 'uncertainty' and one of 'stock price', 'equity price', or 'stock market' in 10 major U.S. newspapers, scaled by the number of articles in each month and paper. The news-based index and the VIX are normalized to a mean of 100 over the period.

**Figure C3: Political slant plays little role in our news-based EPU index**



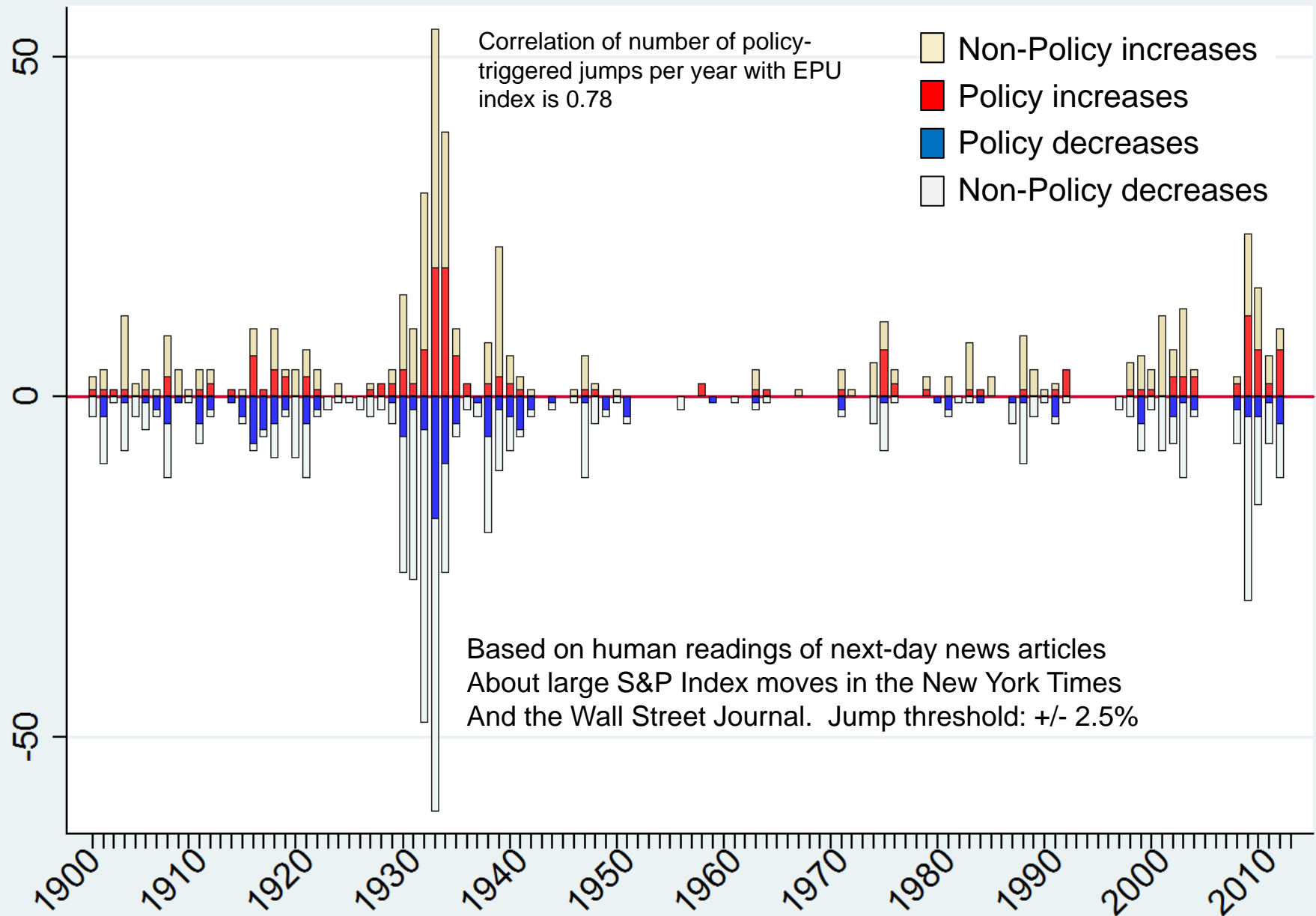
**Source:** Papers sorted into 5 most 'Republican' and 5 most 'Democratic' groups using the media slant measure from Gentzkow and Shapiro (2010).

**Figure C4: Raw Uncertainty and Policy Uncertainty Counts in the Fed's Beige Books and Policy Uncertainty Measure Based on Section 1A (Risk Factors) of Firms' 10-K Filings**



Notes: The left scale shows frequency counts per Beige Book of “uncertainty” and references to policy uncertainty. The right scale reports the percentage of sentences in Section 1A (Risk Factors) of annual 10-K filings that contain one or more of the policy terms listed in Appendix C. The correlation between the BB Policy Uncertainty Count and the EPU index is 0.54.

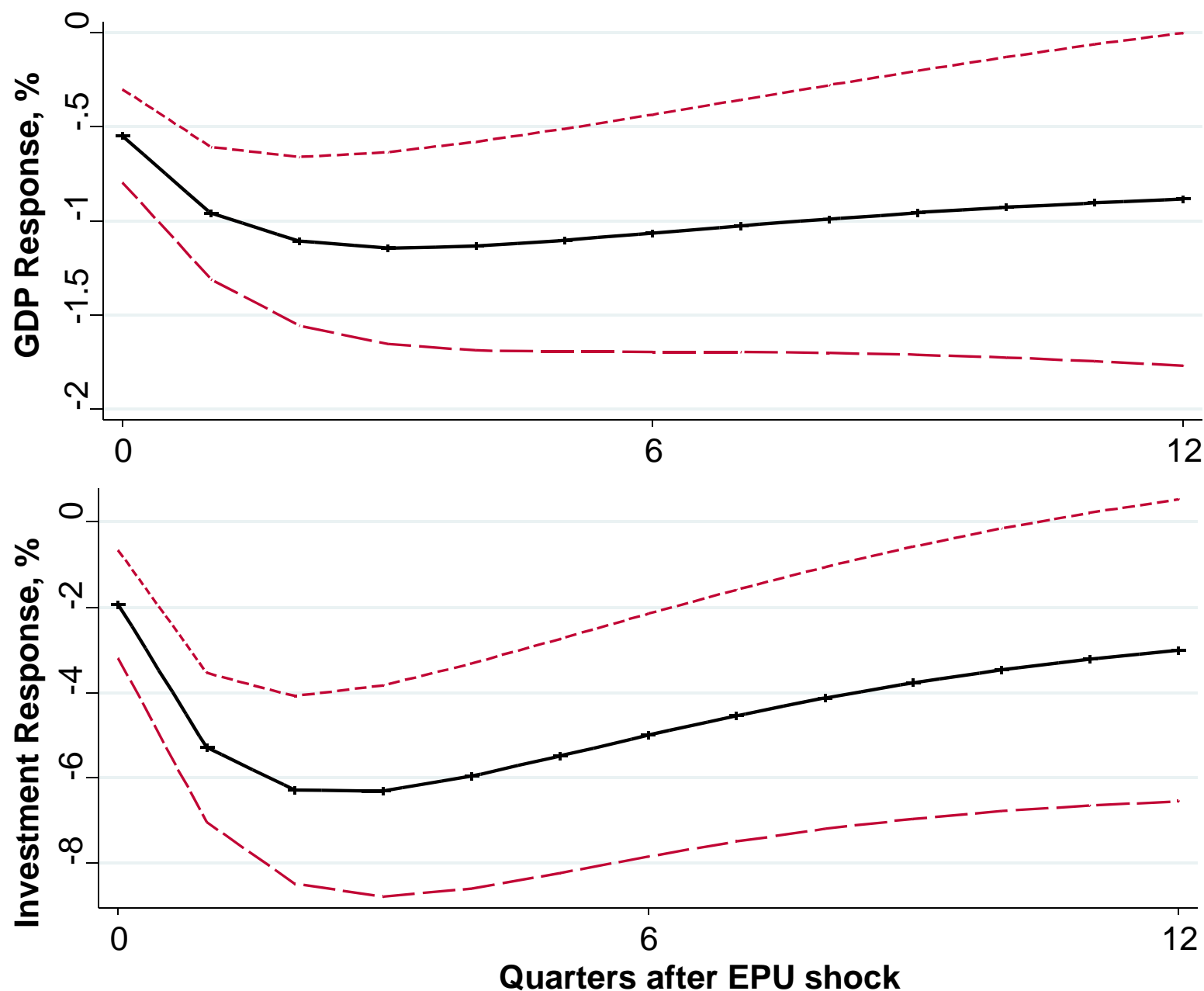
**Figure C5: What triggers large daily stock market moves? 1900-2012**



Reproduced from "What Triggers Large Stock Market Jumps?" by Scott Baker, Nick Bloom & Steven Davis

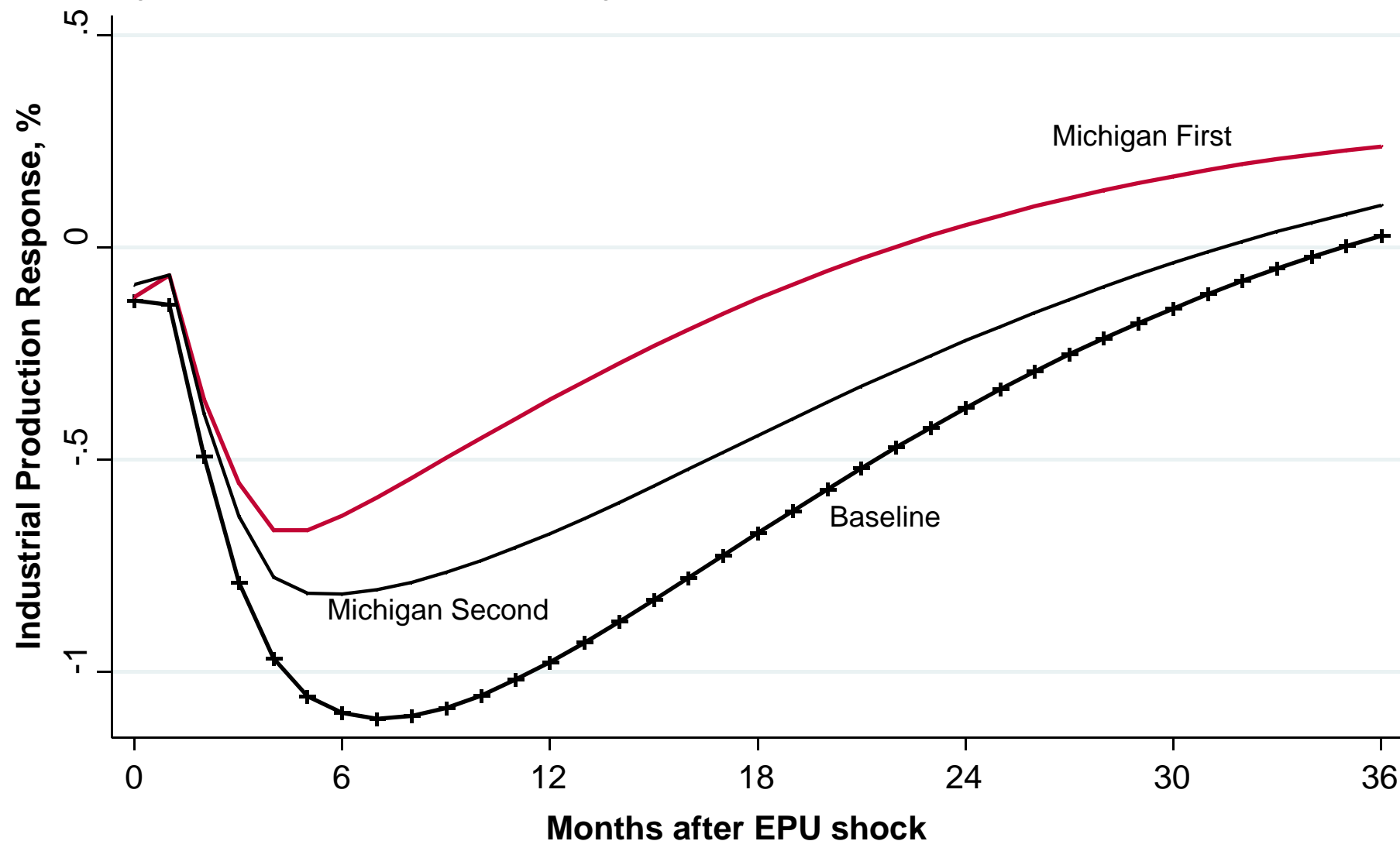


**Figure C6: GDP and Investment Responses to EPU Shock,  
VAR Fit to Quarterly U.S. Data from Q1 1985 to Q4 2012**



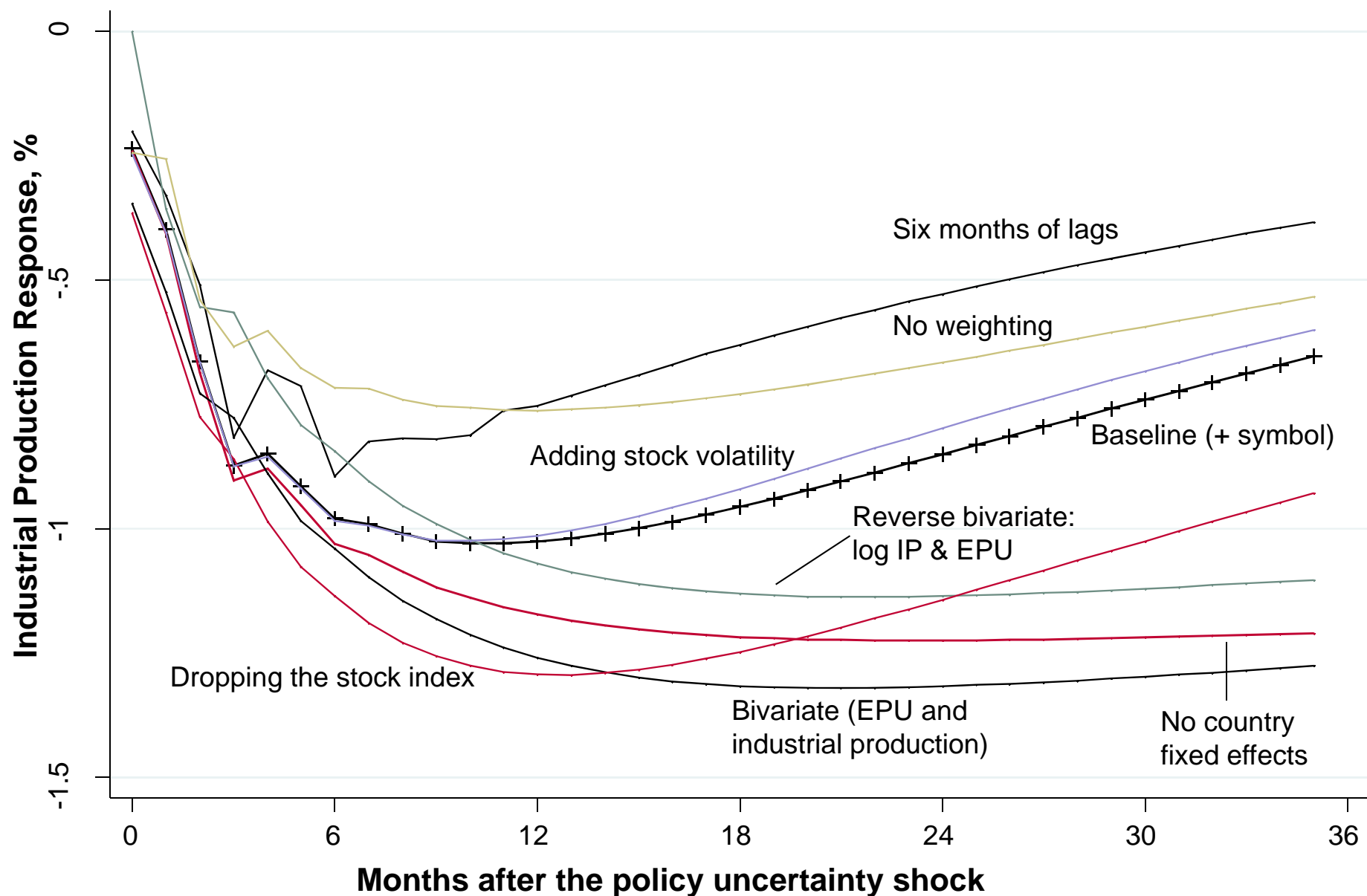
**Notes:** VAR-estimated impulse response functions for GDP and Gross Fixed investment to an EPU innovation equal to the increase in the EPU index from its 2005-2006 to its 2011-2012 average value, with 90 percent confidence bands. Identification based on three lags and a Cholesky decomposition with the following ordering: EPU index, log(S&P 500 index), federal reserve funds rate, log gross investment, log gross domestic product).

**Figure C7: Adding the Michigan Consumer Sentiment Index to VARs Fit to Monthly U.S. Data from January 1985 to December 2012**



**Notes:** VAR-estimated impulse response functions for industrial production to an EPU innovation equal to the increase in the EPU index from its 2005-2006 to its 2011-2012 average value. Identification based on three lags and a Cholesky decomposition. In the baseline, the VAR has the following ordering: EPU index, log(S&P 500 index), federal reserve funds rate, log employment, log industrial production. In the “**Michigan First**” specification the Michigan consumer sentiment index is added first, and in the “**Michigan Second**” it is added after the EPU index.

**Figure C8: Robustness of Twelve-Country Panel VAR Response Functions**



**Notes:** The baseline case involves the same sample period, countries, VAR specification and identification as in Figure 10. The other cases depart from the baseline as indicated. We place realized stock volatility after EPU in the ordering.