Economic Policy Uncertainty: Measures and Applications

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Topic Outline

1. Motivation and Preview
2. Measurement Objective
3. Newspaper-Based EPU Indices: Mechanics
4. Newspaper-Based EPU Indices: Examples & Descriptive Evidence
5. Evaluating Our Measurement Methods
6. Nuts & Bolts I: Sources, archive quality, interface limitations, imputations
7. Nuts & Bolts II: Auditing
8. Econometric Applications
9. Short Tour of Related Indices, Methods, Text Sources and New Survey Instruments
1. Motivation and Preview
Policy Uncertainty Around the Globe

Recent and Ongoing Episodes

- **Europe**: Sovereign debt & banking crises in Eurozone, immigration crisis, Brexit
- **China**: Leadership transition circa 2012, stock market missteps, aggressive sovereignty claims in South China Sea
- **Russia**: Annexation of Crimea, ongoing Ukraine conflict, weak rule of law
- **Turkey**: Failed coup attempt, crackdown
- Brazil, Middle East, ...
Global EPU Index, January 1997 to October 2016

Using data for 16 countries that account for 2/3 of global GDP

Notes: Global EPU calculated as the GDP-weighted average of monthly EPU index values for the US, Canada, Brazil, UK, Germany, Italy, Spain, France, Netherlands, Russia, India, China, South Korea, Japan, Ireland, and Australia, using GDP data from the IMF’s World Economic Outlook Database. National EPU index values are from www.PolicyUncertainty.com and Baker, Bloom and Davis (2016). Each national EPU Index is renormalized to a mean of 100 from 1997 to 2015 before calculating the Global EPU Index.
2016 U.S. Presidential Election

Trump’s surprise win in the U.S. presidential election contest brought greater economic uncertainty in several policy areas, including:

– U.S. trade policy
– U.S. immigration policy
– Institutional independence of Fed
– U.S. support for traditional allies and alliances that undergird the global economic and security order – NATO, South Korea, Japan, ...
U.S. Daily Economic Policy Uncertainty Index 1 June to 16 November 2016

Brexit

Fiscal Cliff – 7 Days Ending 31 Dec 2012: 332

Election

November 13
November 9
November 8

Politics and Economic Uncertainty

• These recent examples, drawn from many parts of the world, suggest that governments and political processes are important sources of economic uncertainty.

• Policy-related uncertainty also arises as a consequence of major economic shocks and disruptions. Example: The Global Financial Crisis of 2008–09 confronted policymakers with extraordinary and complex challenges → great uncertainty about how policymakers should and would respond to the challenges, and what would be the economic consequences.

• Poor economic performance can fuel populist political forces, raising policy uncertainty: Trump, Le Pen, Brexit, rise of far-right political parties in Europe. See Funke et al. (2016).
How Might High Policy Uncertainty Harm Economic Performance? By

- Causing businesses to delay or forego investment and hiring when they are costly to reverse
- Raising the cost of debt and equity finance, thereby discouraging investment
- Causing households to behave more cautiously, cutting back on spending
- Prompting excessive caution among risk-averse managers
- Intensifying monopoly pricing distortions.
- Undermining confidence?
2. Measurement Objective
Making Progress in Understanding the Role of Economic Policy Uncertainty

“The first essential step in the direction of learning any subject is to find principles of numerical reckoning and practicable methods for measuring some quality connected with it.”

Lord William Thompson Kelvin, 1883
What Do Our Policy Uncertainty Measures Seek to Capture?

All of the following:

• Uncertainty about *who* will make economic policy decisions – e.g., who will win the next election?
• Uncertainty about *what* economic policy actions decision makers will undertake, and *when*.
• Uncertainty about the economic *effects* of policy actions – past, present and future actions
• Economic uncertainty induced by policy inaction
• Uncertain economic ramifications of national security and other policy matters that may not be mainly economic in character
3. Newspaper-Based EPU Indices: Mechanics
Our Economic Policy Uncertainty Indices rely on computer-automated newspaper searches

How it works for the United States:

- For 10 major US papers, get monthly counts of articles that contain at least one word from each of three term sets:
  
  **E**: \{economic or economy\}
  
  **P**: \{regulation or deficit or “federal reserve” or congress or legislation or “white house”\}
  
  **U**: \{uncertain or uncertainty\}

  Include “the Fed”, “regulatory” and other variants.

- Scale the EPU count for each paper and month by the count of all articles in the same paper and month

- Standardize each paper’s scaled count to unit St. Dev., then sum over the 10 papers by month to get the U.S monthly index
Constructing our Monthly Newspaper-Based EPU Index for the United States

Newspapers:
- Boston Globe
- Chicago Tribune
- Dallas Morning News
- Los Angeles Times
- Miami Herald
- New York Times/Houston Chronicle
- SF Chronicle
- USA Today
- Wall Street Journal
- Washington Post

Note: We use Access World News Newsbank Service when constructing a daily EPU Index, because the daily index requires a higher density of news sources.
4. Newspaper-Based EPU Indices: Examples & Descriptive Evidence

-- National EPU indices
-- Global EPU index
-- Historical EPU indices
-- The Brexit uncertainty shock
-- Electoral patterns in the data
-- Category-specific EPU indices
-- Immigration fears and policy uncertainty
More Newspaper-Based EPU Indices

• Monthly EPU indices for 17 countries that account for 2/3 of global output.
  – Several more countries in the works
• Historical EPU indices back to 1900 for the US and the UK
• U.S. category-specific EPU indices
• Daily EPU indices for the US and UK
• Daily Equity Market Uncertainty index
• Immigration Fear and Policy Uncertainty indices for the US, France, Germany, UK

Downloadable and regularly updated at http://www.policyuncertainty.com
Economic Policy Uncertainty Index for Australia, 1998 to April 2016

Reproduced from “Policy Uncertainty in Japan” by Arbatli, Davis, Ito, Miake and Saito, 2016.
Notes for Japan EPU Index

- The index reflects scaled frequency counts of articles in Yomiuri, Asahi, Mainichi, and Nikkei that contain at least one term in each of three categories: (E) ‘economic’ or ‘economy’; (P) ‘tax,’ ‘government spending,’ ‘regulation,’ ‘central bank’ or certain other policy-related terms; and (U) ‘uncertain’ or ‘uncertainty’.


- Note: Shaded areas indicate recession dates.
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.
EPU Index for Russia, October 1992 to August 2014

Economic Policy Uncertainty Index for China

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.
Global EPU Index, January 1997 to October 2016

Notes: Global EPU calculated as the GDP-weighted average of monthly EPU index values for the US, Canada, Brazil, UK, Germany, Italy, Spain, France, Netherlands, Russia, India, China, South Korea, Japan, Ireland, and Australia, using GDP data from the IMF’s World Economic Outlook Database. National EPU index values are from www.PolicyUncertainty.com and Baker, Bloom and Davis (2016). Each national EPU Index is renormalized to a mean of 100 from 1997 to 2015 before calculating the Global EPU Index.
Figure 2: US Historical Index of Economic Policy Uncertainty

Adding “tariff” and “war” to the P term set

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 2. An Upward Drift in Policy-Related Economic Uncertainty

Newspaper-Based Index of Economic Policy Uncertainty (EPU)

EPU Scaled by the Number of Articles About Economy, Business and Industry

Source: Baker et al. (2014). Data are annual averages of monthly values from 1949 to 2012.
Why the big run-up in U.S. EPU? Unclear, but see our work with political scientists Jonathan Rodden and Brandice Canes-Wrone.

Why Has US Policy Uncertainty Risen Since 1960?†

By Scott R. Baker, Nicholas Bloom, Brandice Canes-Wrone, Steven J. Davis, and Jonathan Rodden*

We consider two classes of explanations for the rise in policy-related economic uncertainty in the United States since 1960. The first stresses growth in government spending, taxes, and regulation. A second stresses increased political polarization and its implications for the policy-making process and policy choices.

I. Rising Policy Uncertainty

There appears to be a strong upward drift in policy-related uncertainty after 1960. As evidence, Figure 1 plots a newspaper-based index of economic policy uncertainty (EPU) for the United States, showing a secular rise over the last
UK government share of GDP is roughly flat since the 1950s (unlike the US, where it has roughly doubled)

Chart 1.1: Total public sector spending and receipts
Page counts do not include executive memoranda, regulatory guidance, and other regulatory “dark matter.”

Merely describing the U.S. tax code
Takes another 70,000 pages – 52 bibles!

Updated from Davis (2015), who draws on Dawson and Seater (2013) and Crews (2016)
The Brexit Uncertainty Shock

- A surprise referendum outcome
- It triggered a huge spike in UK EPU
- Global EPU reverberations
- But concerns about Brexit-related uncertainty have abated rapidly
The Brexit Shock and Its Immediate Wake, Daily Data

The Brexit Shock and Its Immediate Wake, Daily Data

Massive Surge In UK EPU!!

A Big Surprise!!


But EPU Surge Largely Reverses within 2 Weeks
The Brexit Shock and Its Immediate Wake, Daily Data

Fast Recovery in Equity Markets

Large Depreciation In Pound Persists

1. Brexit referendum outcome was a big surprise and a massive shock to UK EPU, with global reverberations.

2. But (concerns about) Brexit-related uncertainty dissipated very rapidly, according to our EPU indices.

3. The British Pound fell more than 10% against the US Dollar in wake of Brexit referendum, and it remains down.

4. Equity markets, however, rebounded within a few weeks.

5. Quantifying the likely near-term output effects of Brexit is really, really hard – at least for us.

6. For industrial production, our VAR models suggest a peak negative effect of Brexit uncertainty shock of about minus 2 log points 6-12 months later.

7. Best guess for peak GDP response is about -1 log point, after considering less volatile nature of GDP, muting effect of Pound depreciation and aggressive BOE response.
Electoral Patterns in the Data

1. U.S. EPU was high in the months surrounding the first elections of Bill Clinton, George W. Bush, ...

2. Looking at 62 national elections in 11 countries, my research with Baker and Bloom finds statistically significant evidence of elevated EPU around national leadership elections more generally.

3. But the estimated effect of elections on EPU is modest – roughly a 20 percent increase on average, and a bit more for close elections.

4. Why such a modest effect for national leadership elections? Perhaps because the policy stakes are also modest – in most cases.
U.S. Daily Economic Policy Uncertainty Index
1 June to 16 November 2016

Why was US EPU subdued in advance of the presidential election? Four reasons:

1. The smart(?!?) money said Clinton would win with high probability.
2. Clinton is a known quantity – she’s been on the national policy scene for 25+ years.
3. She’s also a status quo candidate who was seen as unlikely to implement large, abrupt departures from Obama’s policies.
4. The Republicans were seen as likely to retain control of the House, Senate or both, preserving the recent pattern of divided government and curtailing the scope for major policy shifts.
The 2016 U.S. Presidential Election

1. Trump and Clinton were far apart on many major policy issues: immigration, trade, taxes, foreign policy, etc. Not Tweedledee vs. Tweedledum.

2. Trump is a wild card – no track record as a policy maker; little in the way of a consistent, coherent set of policy principles; and a history of intemperate remarks. He also seems to regard unpredictability as an attractive philosophy of leadership and governing.
Notes: The index reflects the frequency of newspaper articles about economic policy uncertainty and financial regulatory matters, as indicated by terms like “bank(ing) supervision,” “Glass-Steagall,” and “Dodd-Frank.” Data are from Baker, Bloom and Davis (2015) and are available and updated monthly at www.PolicyUncertainty.com. Normalized to a mean of 100 from 1985 to 2009.
Selected category-specific EPU Indices, Quarterly

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.
Which policy categories most account for high U.S. EPU in 2008-2012? Newspaper articles point to concerns about fiscal and healthcare policies.

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<th>1985-2007</th>
<th>2008-2012</th>
<th>Change</th>
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<tr>
<td>Taxes</td>
<td>35.2</td>
<td>61.1</td>
<td>25.9</td>
</tr>
<tr>
<td>Health care</td>
<td>12.7</td>
<td>33.3</td>
<td>20.6</td>
</tr>
<tr>
<td>Regulation</td>
<td>14.9</td>
<td>28.4</td>
<td>13.6</td>
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<tr>
<td>Social Security</td>
<td>10.3</td>
<td>19.4</td>
<td>9.1</td>
</tr>
<tr>
<td>Government spending</td>
<td>15.0</td>
<td>23.9</td>
<td>8.9</td>
</tr>
<tr>
<td>Sovereign debt, currency crisis</td>
<td>1.4</td>
<td>2.8</td>
<td>1.4</td>
</tr>
<tr>
<td>Monetary policy</td>
<td>29.0</td>
<td>27.6</td>
<td>-1.5</td>
</tr>
<tr>
<td>National security</td>
<td>25.3</td>
<td>19.9</td>
<td>-5.4</td>
</tr>
</tbody>
</table>

Table construction: First, look at EPU articles and count those that contain category-specific terms. Second, express the category counts as a percent of the average EPU article count from 1985 to 2012. We use Newsbank’s coverage of about 1,000 US newspapers for this exercise. See Table 1 in Baker, Bloom and Davis (2015) for a more detailed analysis.
Immigration Fears and Policy Uncertainty
Constructing Migration-Related Indices

**Five term sets**

E, P and U, as before, plus:

F(ear): {anxiety, panic, bomb, fear, crime, terror, worry, concern, violent }


- To construct a Migration Fear Index, count articles that contain at least one term from each of M and F.
- To construct a Migration Policy Uncertainty Index, count articles that contain at least one term from each of M, E, P and U.
- Scale the counts and normalize in the same way as before.
- We have constructed Migration Fear and Policy Uncertainty Indices for France, Germany, the U.K. and the U.S.
Notes: The Migration Policy Uncertainty Index reflects scaled quarterly counts of articles in Le Monde that satisfy the M, E, P and U criteria specified in the text. Similarly, the Migration Fear Index reflects scaled quarterly counts that satisfy the M and F criteria. We obtain article counts on 30 November 2015 and normalize each index to 100 from 1995 to 2011.
Notes: The Migration Policy Uncertainty Index reflects scaled quarterly counts of articles in Frankfurter Allgemeine Zeitung and Handelsblatt that satisfy the M, E, P and U criteria. Similarly, the Migration Fear Index reflects scaled quarterly counts that satisfy the M and F criteria. We obtain article counts on 30 November 2015 and normalize each index to 100 from 1995 to 2011.
Notes: The Migration Policy Uncertainty Index reflects scaled quarterly counts of articles in the Financial Times and the Times of London that satisfy the M, E, P, and U criteria. Similarly, the Migration Fear Index reflects scaled quarterly counts that satisfy the M and F criteria. We obtain article counts on 30 November 2015 and normalize each index to 100 from 1995 to 2011.
Migration Fear and Policy Uncertainty Indices, United States, 1995-2015

Notes: The Migration Policy Uncertainty Index reflects scaled quarterly counts of articles in US newspapers indexed by the Access World News Newsbank database that satisfy the M, E, P and U criteria specified in the text. Similarly, the Migration Fear Index reflects scaled quarterly counts that satisfy the M and F criteria. We obtain article counts on 30 November 2015 and normalize each index to 100 from 1995 to 2011.
What Do The Migration Indices Tell Us?

• European countries show unprecedented levels of migration-related worries in late 2015.
• The United States shows a much more modest elevation of migration-related fears in late 2015, despite much attention to immigration and border control issues among U.S. presidential candidates.
• Since 2005, migration-related fears have trended upward strongly in the United Kingdom (alongside rising levels of actual migration)
• Migration related fears rose in France around 2005, while migration-related fears in Germany do not show persistent upward movements until 2014.
What Do The Migration Indices Tell Us?

• The data strongly suggest that migration-related fears can spillover into policy uncertainty.
• The “spillover” effect illustrates a broader pattern that we see in our measures of overall economic policy uncertainty for a dozen countries:
  – Large unforeseen shocks can present policy makers with extraordinary challenges.
  – Questions about how policy makers will respond and what will be the consequences then become an important source of economic uncertainty.
What Do The Migration Indices Tell Us?

• The Schengen zone arrangements do not seem well-equipped to handle Europe’s huge recent immigration flows, contributing to the high levels of migration-related fears and policy uncertainty.

• This experience and serial Eurozone crises in recent years illustrate how the institutional setting and policy-making environment can influence the extent to which negative shocks and developments lead to bad outcomes, difficult policy challenges, and high levels of policy uncertainty.
5. Evaluating Our Measurement Methods
Two Basic Measurement Concerns

**Suitability:** Whether an accurate count for news articles about a particular type of uncertainty provides a good indicator for that type of uncertainty.

**Accuracy:** Whether specific text-string search criteria accurately identify the set of articles that discuss a certain type of uncertainty, e.g., policy-related economic uncertainty.
Assessing Suitability Concern

_Idea:_ Apply news-based approach to a concept of uncertainty for which we have external, market-based evidence.

_Implimentation:_ Compare VIX measure of uncertainty about future equity returns to a news-based index of equity market uncertainty, with search terms as follows:

\{economic OR economy\} AND
\{uncertain OR uncertainty\} AND
\{"stock price" OR "equity price" OR "stock market"\}
A) Proof-of-Concept: Comparing a newspaper-based index of equity market uncertainty to the VIX.

The newspaper-based index of *Equity Market Uncertainty* uses our E and U term sets but replaces the P set with “stock price”, “equity price”, and “stock market”

**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.
Assessing Accuracy Concern

Idea: Deploy intelligent, trained, motivated humans to read and code randomly selected articles. Then optimize computer-automated article classifications in light of the human classifications.

Implementation:

- Informal, small-scale audits: A key input into high-quality newspaper-based indices
- Formal audit at scale: Very useful, but resource intensive to perform. Details in Section 7.
- Other approaches
B) Large-Scale Human Audit Study

Teams of RAs read 12,000 randomly selected newspaper articles to code them as to “economic uncertainty”, “economic policy uncertainty” and more according to a 65-page audit guide.

FAQ

1. Do you need to code an article as EPU if it includes a single word like “uncertainty”?

No. An article must mention an economic uncertainty event, economic policy uncertainty event, etc...

2. In the unlikely event that an article mentions economic uncertainty, economic policy uncertainty, etc... in passing but does not actually discuss them, should it be coded as EPU = 0?

Yes, it should be coded as EPU = 0.

3. What happens if an article mentions an event that occurred before the study started?

It should be excluded from the study.

4. Given that the outcome of government policy is always uncertain, at some level, does any mention of a new or proposed policy constitute EPU = 1?

No. An article must mention an economic uncertainty event, economic policy uncertainty event, etc...

Economic Policy Uncertainty

Audit Methodology: Main Steps

1. Download all NY Times, LA Times, and SF Chronicle articles from 1985 to 2012 that pass our Economic Uncertainty Event screening.
2. Assign 84 of the sampled articles for each paper to Kyle and 84 to Sophie. Call these subsamples Sub(Name, Paper).
3. Assign 84 of the sampled articles for each paper to Kyle and 84 to Sophie. Call these subsamples Sub(Name, Paper).
4. Review the subsamples of articles per paper.
5. In sum, audit 6,240 articles per paper.
6. Last, review the articles for accuracy and consistency.

Auditing the Sampled Articles

3. If yes to 2, then identify the policy category (checking all that apply):
   - Monetary policy
   - Fiscal policy
   - Taxes
   - Labor regulations
   - Legal policy
   - Competition policy
   - Government spending
   - Health care programs and regulations
   - National security and terrorism
   - Trade policy
   - Energy & environmental regulation, natural resources and commodities
   - Entitlement programs, social safety net, welfare programs
   - Financial regulation (including banking and equity markets)
   - Political conflict and leadership changes
   - Sovereign debt, exchange rate policy, foreign reserves
   - Other policy matters (specify)

4. Code other aspects of policy uncertainty treated in the article: direction of change, nature of policy uncertainty (is it about who, actions, or effects?), and whether it discusses policy concerns in the United States or foreign countries.
Selecting a Preferred Term Set


• Consider additional permutations that replace terms like “policy” and “government” with multi-word terms like “government policy”

• Interpreting the human coding as truth, select the term set that minimizes the sum of false positive and false negative error rates
C) Political Slant? Compare 5 most Republican and 5 most Democratic papers – they look very similar.

Papers sorted into 5 most ‘Republican’ and 5 most ‘Democratic’ groups using the media slant measure from Gentzkow and Shapiro (2010).
But Are Newspapers Reliable? What about Other Text Sources?

- Newspaper articles: Written by amateurs for the average Joe
- FOMC Beige Books: Written by experts for experts
- SEC filings by listed firms: Prepared by accountants and lawyers to meet regulatory disclosure requirements
- Earnings conference calls with senior management at publicly listed firms
D) 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.
## Beige Book also highlights fiscal policy concerns

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<td><strong>Sum of Policy &amp; Politics Categories</strong></td>
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<td><strong>9.3</strong></td>
<td><strong>2.2</strong></td>
<td><strong>5.2</strong></td>
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<td><strong>0.8</strong></td>
<td><strong>10.0</strong></td>
<td><strong>2.5</strong></td>
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Figure C5: Importance of Policy Risk Factors Based on Their First Appearance in Part 1a of Firms’ 10-K Filings

The vertical scale shows the fraction of Part 1a that must be read before encountering a discussion of policy risks. Lower values mean greater importance of policy risks.
E) **Market-Use Test**

Market use underscores the information value of our data:

I) Many policy organizations and financial institutions use our data including Goldman Sachs, Citibank, JP Morgan, Wells Fargo, IMF, central banks, and more. (see [www.policyuncertainty.com](http://www.policyuncertainty.com)).

I) Blackrock has its own in-house team that has picked up on our work and adopted methods similar to ours.

I) Bloomberg, FRED, Reuters and Haver stream our data for their business clients and other users.
6. Nuts & Bolts I: Sources, archive quality, interface limitations, imputations
Digital Archives and Interfaces

- Proquest
- Factiva
- Newsbank’s Access World News
- Individual newspapers w/ archive & interface
- Lexis-Nexis
- Other news aggregators (often language- or country-specific)

We rely mainly on the first four sources above, but our basic approach is to use any available source with a high-quality archive and a workable search interface.
Why build indices from article frequency counts?

- Because more sophisticated methods involve repeated and intensive interrogation of the text.
- Not feasible unless text resides on local disk or you have some other form of high-capacity, high-speed access to the digital archive.
- Thus far, we have opted for simple, transparent methods that can applied to very large text sources across many interfaces, newspaper, countries and time periods.
Minimal Interface Requirements

1. Search-by-date capabilities
2. Boolean operators (AND, OR, etc.)
3. Allows for adequate number of search terms.
4. Searches yield an article frequency count
5. Can be automated
   – We sometimes work with interfaces that require manual search entry, when automation is infeasible.
   – Manual approach is time-consuming, costly to revise/improve, more prone to error, and not conducive to formal audits

Note: Interface may not operate as advertised. So it’s important to check how it handles plurals, other word variants, operators, etc.
Evaluating the Digital Archive

It’s essential to evaluate the completeness and quality of the digital archive. A first step is to plot the natural log of the total monthly article count for each newspaper. This step helps identify:

1. Short or log gaps in archive coverage
2. Interface issues
3. Shifts in archive coverage (e.g., inclusion or exclusion of various editions and sections)
4. Newspaper shutdown periods
5. Major shifts in newspaper length or coverage that might call for some adjustment in the index construction
South Korea as an Example

• South Korea offers an interesting case study of several practical issues that arise in constructing a national EPU index.
• The next few slides illustrate a few of the issues
• See "South Korea EPU Memo” by Jessica Yu Kyung Koh for a fuller discussion.
<table>
<thead>
<tr>
<th>Category</th>
<th>English Terms</th>
<th>Korean Terms</th>
<th>In Korean Characters</th>
</tr>
</thead>
<tbody>
<tr>
<td>U</td>
<td>uncertainty OR uncertain</td>
<td>bulhwaksilsung OR bulhwaksil</td>
<td>불확실성 OR 불확실</td>
</tr>
<tr>
<td>E</td>
<td>economic OR economy commerce</td>
<td>gyeongje OR gyeongjeui sangup OR muyeok</td>
<td>경제 OR 경제의 상업 OR 무역</td>
</tr>
<tr>
<td>P</td>
<td>government &quot;Blue House&quot; congress authorities legislation tax regulation &quot;Bank of Korea&quot; &quot;central bank&quot; deficit WTO law/bill &quot;ministry of finance&quot;</td>
<td>jeongbu Chungwade gukhoe dangguk jejeong OR jejeongbu OR ibbub se gyuje OR tongje OR gyejeong Hankukeunhaeng OR Haneun jungangeunhaeng jukja OR bujok WTO OR Segye muyeok gigu bub OR buban gihwaekjaejungbu OR gijaebu</td>
<td>정부 정의의 정회 당국 제정 OR 제정법 OR 입법 세 규제 OR 통제 OR 규정 한국은행 OR 한은 중앙은행 적자 OR 부족 WTO OR 세계 무역 기구 법 OR 법안 기획재정부 OR 기재부</td>
</tr>
<tr>
<td>Newspaper Name</td>
<td>Political Orientation</td>
<td>Type</td>
<td>Archive</td>
</tr>
<tr>
<td>---------------</td>
<td>-----------------------</td>
<td>---------------</td>
<td>--------------------------------</td>
</tr>
<tr>
<td>Chosun Ilbo</td>
<td>Conservative</td>
<td>Daily News</td>
<td>Chosun Archive</td>
</tr>
<tr>
<td>Chungang Ilbo</td>
<td>Conservative</td>
<td>Daily News</td>
<td>Chungang Website</td>
</tr>
<tr>
<td>Donga Ilbo</td>
<td>Conservative</td>
<td>Daily News</td>
<td>1. Donga Archive</td>
</tr>
<tr>
<td>Hankook Ilbo</td>
<td>Moderate</td>
<td>Daily News</td>
<td>Big Kinds</td>
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<td>2. Big Kinds</td>
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<td>2. Big Kinds</td>
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<tr>
<td></td>
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<td>2. Big Kinds</td>
</tr>
<tr>
<td>Korea Economic</td>
<td>Conservative</td>
<td>Economic</td>
<td>Big Kinds</td>
</tr>
</tbody>
</table>
Figure 1: Monthly Information on Raw EPU and Total Counts (Donga Ilbo)

- Multiple shutdown periods
- Much use of Chinese characters before 1980
- Naver translates Chinese to Korean characters
- Donga archives do not
Multiple shutdown periods

Discrepancies between archives
Figure 5: Monthly Information on Raw EPU and Total Counts (Hankook Ilbo)

No shutdown months but large swings in log(total count)
Figure 6: Monthly Information on Raw EPU and Total Counts (Korea Economic)

No shutdown months but large swings in log(total count)
5.2 Identification of Abnormal Months

We use the following rule to identify abnormal months for each newspaper in the post-1990 period: Let $N(t)$ be the total newspaper article count in month $t$, and let $N(t - 15, t - 4)$ denote the average monthly article in the same paper from 15 months earlier to 4 months earlier. If $\frac{N(t)}{N(t - 15, t - 4)} < 0.3$, we identify the month $t$ as an "abnormal month."

The following list shows abnormal months for each newspaper over the years 1990-2015:

- **Hankook Ilbo:** August 2014


- **Korea Economic Daily:** March - June 1999, September - December 2015, January 2016
Imputations (South Korea)

Let $E^i_t$ be the EPU rate for newspaper $i$ at month $t$. Let $T^i$ be the set of abnormal months for newspaper $i$. In order to impute values for the EPU rate during the abnormal months, we first regress EPU rates of a newspaper with abnormal month on EPU rates of newspapers without any abnormal months (which are Donga Ilbo, Kyunghyang, and Hankyoreh). That is,

$$E^i_t = \alpha + \beta_1 E^{Donga}_t + \beta_2 E^{Kyunghyang}_t + \beta_3 E^{Hankyoreh}_t + \varepsilon^i_t, \forall t \notin T^i \quad (1)$$

Note that we do not include the abnormal months when estimating the above regression equation. Once Equation 1 is estimated, we impute the EPU rates for abnormal months using the following equation:

$$\tilde{E}^i_t = \hat{\alpha} + \hat{\beta}_1 E^{Donga}_t + \hat{\beta}_2 E^{Kyunghyang}_t + \hat{\beta}_3 E^{Hankyoreh}_t, \forall t \in T^i \quad (2)$$

where $\hat{\alpha}, \hat{\beta}_1, \hat{\beta}_2$, and $\hat{\beta}_3$ are the estimated coefficients from Equation 1.
**Economic Policy Uncertainty Index for South Korea, Jan. 1990 to Aug. 2016**

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 of “Measuring Economic Policy Uncertainty” by Baker, Bloom and Davis. The series is normalized to mean 100 from 1995 to 2014.
7. Nuts & Bolts II: Auditing
Audit Process Overview

1. For our QJE paper, we first read and discussed a few hundred randomly selected “EU” articles to develop a coding template, training process, and draft audit guide.

2. Pilot study of 2,000 EU articles by authors and RAs to improve training process, refine coding template, expand and improve audit guide, and refine sampling methods.

3. Main audit study of EU articles (basis for analysis):
   - Training and review process for all auditors
   - 65-page audit guide (available on the web)
   - Audit team meetings every week or two over 18 months to address questions, review “hard calls,” maintain esprit de corps, and monitor performance
   - Auditors read and coded 12,000+ articles
   - We randomized article selection, order of presentation to auditors, assignment of articles to multiple auditors
How We Use the Audit Study Results

1. Identify candidate “P” terms:
   - When auditor codes EPU=1, he or she also records policy terms that appear in article’s discussion of EPU.
   - Candidates: 15 frequently appearing P terms

2. Consider ~32,000 term-set permutations involving 4 or more candidate P terms. Choose the P term set that minimizes the sum of false positive and false negative error rates relative to the human EPU classifications.
   - This optimization yields our baseline P term set.
   - We do not use time-series variation to select P term set.
   - To our surprise, we were unable to develop simple compound text filters (e.g., {government AND tax}) that improve on our baseline term set.

3. Time-series comparisons of humans and computers (next 2 slides) and additional empirical results (following slide)
Economic Policy Uncertainty Index

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.

Correlation = 0.86
Human and Computer EPU Indices, 1900-2010, Annual

Correlation=0.93

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.
Other Selected Results from the Audit Study

- Only 5% of articles with $EPU^H = 1$ mainly discuss actual or prospective declines in policy uncertainty.
- 10% of $EPU^H = 1$ articles discuss uncertainty about who will make economic policy decisions, 68% discuss uncertainty about what policies will be undertaken or when, and 47% discuss uncertainty about the effects of past, present or future policy actions.
- The who share of $EPU^H = 1$ triples in presidential election years as compared to other years → the nature of policy uncertainty shifts substantially over the election cycle.
- 32% of $EPU^H = 1$ articles mention policy matters in other countries, often alongside domestic policy concerns.
Is a Large-Scale Human Audit Essential For Constructing a Useful Index?

• No. We get by with informal audits in most cases. But we still draw on learnings from the large-scale U.S. audit.

• Two considerations drove us to the large-scale U.S. audit:
  – We covered 112 years, raising greater concerns about changes in the economy, policy issues and language.
  – We sought to characterize the time-series properties of the computer-generated errors. This objective greatly increases the necessary size of an audit sample.

• In other instances, we have found that a formal audit of 500-1,000 articles is enough to be extremely useful in evaluating/refining the term set and getting a better index.

• For an alternative approach to term-set selection/refinement, see Hassan, Hollander, van Lent and Tahoun (2016).
8. Econometric Applications:

-- Aggregate time-series analysis
-- Firm-level panel regressions
National Time-Series Evidence

- Include Monthly EPU Indices in Vector Autoregressive (VAR) statistical models of the sort that macroeconomists routinely use to characterize dynamic co-movements in aggregate data.
- Fit to monthly and quarterly data for the United States and to a dozen countries in a panel VAR.
- Examine Impulse Response Functions to EPU shocks (i.e., Cholesky innovations).
- **Main Question:** What do EPU shocks portend for future movements in output growth, investment rates, employment growth, etc.?
Figure 8: Industrial Production and Employment Responses to EPU Shock, VAR Fit to Monthly U.S. Data

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. Fit to monthly data from 1985 to 2014.
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 C8: Adding the Michigan Consumer Sentiment Index to VARs Fit to Monthly U.S. Data

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. Fit to data from 1985 to 2014.
US VAR for Impact on GDP and Investment (quarterly)

**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). Fit to data from 195 to 2014.
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 2014, where available.
Figure C9: 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 X. The other cases depart from the baseline as indicated. We place realized stock volatility after EPU in the ordering.
Summary of National Time-Series Evidence

• Positive EPU shocks foreshadow deteriorations in macroeconomic performance, as reflected by investment, employment and output measures. Many other studies find similar results using our measures.

• Dynamic responses are material, but moderate, in size.

• The right interpretation of these statistical results is unclear. Two possibilities (not the only two):
  – Higher EPU causes the negative statistical effects
  – EPU shocks coincide with other negative developments that are not (fully) captured by the other variables in our statistical model, and the other developments cause the deterioration.
Firm-Level Evidence

• Micro data offer more scope to control for confounding factors and to identify causal effects.
• We use firm-level micro data to investigate the effects of EPU on firm-level stock-price volatility, investment rates and employment growth rates.
• Our approach exploits large differences across firms in exposure to policy factors (government spending and regulations).
• We investigate whether firms with greater exposure to policy risks see larger responses to movements in our EPU index.
Exploiting differences across firms in share of revenues from sales to the federal government.


- Guided Missiles and Space Vehicles: 78%
- Health Services: 44%
- Ordnance and Accessories: 39%
- Search, Detection, Navigation,… Aeronautical Systems: 27%
- Engineering Services: 21%
- Aircrafts and Parts: 20%
- Ship and Boat Building and Repairs: 15%
- Books, Loose Leaf Binders, and Bookbinding: 10%
- Heavy Construction: 9%

Direct sales to federal government account for a small share of revenues in most other industries.
Measuring Firm-Level Policy Exposure Intensity

Main Approach: First, compute revenue share of government purchases at SIC3 level from 2000-2013. Second, compute firm-level exposure as revenue-weighted mean of its industry exposures using Compustat line of business data. Time-averaged measures, constant at the firm level.

- Similar results when computing firm-level exposure directly, letting firm-level exposure vary by year, using IO matrix.

Two Alternative Approaches:

1. Measure exposure by slope coefficient in regression of firm’s daily stock returns on daily EPU index from 1985-1995, which pre-dates the regression sample period.

2. Quantify policy risk exposure using textual analysis of 10-K filings. Specifically, compute each firm’s 2006-2013 average share of sentences in Section 1A (Risk Factors) that reference policy matters.
Firm-level panel regressions for option-implied 30-day stock-price volatility, basic specification

\[ Y_{it} = F_i + P_t + \alpha \cdot \text{Exp}_i \cdot (G/Y)_t + \beta \cdot \text{Exp}_i \cdot \text{EPU}_t + \epsilon_{i,t} \]

- \( Y_{it} \): Stock-price volatility at firm-quarter level, average of daily values
- \( F_i \): Firm fixed effects
- \( P_t \): Period fixed effects
- \( \alpha \cdot \text{Exp}_i \cdot (G/Y)_t \): Firm policy exposure \( \times \) government purchases share of GDP (another 1st moment firm-level control variable)
- \( \beta \cdot \text{Exp}_i \cdot \text{EPU}_t \): Firm policy exposure \( \times \) EPU Index (2nd moment interaction effect of interest)

We weight observations by firm-level sales in all regressions.

i=firm, t=quarter, 1996-2012 sample period, clustering by i when estimating standard errors
Table 2: Firm-Level Effects of Policy Uncertainty on Option-Implied Stock Price Volatility

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

Notes: The sample contains 136,742 observations on 5,624 firms from 1996 to 2012. The dependent variable is the 30-day implied vol.

Column 2: Basic specification
Column 4: Horse race between EPU*Exposure and VIX*Exposure
Column 6: Horse race between EPU*Exposure and EU*Exposure
Column 7: Includes category-specific EPU indices
Robustness Checks on Results for Firm-Level Stock-Price Volatility

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

<table>
<thead>
<tr>
<th>Specification</th>
<th>(1) Realized Volatility</th>
<th>(2) 182-day Implied Volatility</th>
<th>(3) Add Purchase Forecast</th>
<th>(4) Add 12 qtrs Future Purchases</th>
<th>(5) Firm-level Intensity</th>
<th>(6) Belo et al. (2013) Intensity</th>
<th>(7) Beta Intensity</th>
<th>(8) 10-K Risk Measure</th>
<th>(9) $500m+ Sales Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(EPU)×Intensity</td>
<td>0.346*** (0.089)</td>
<td>0.178*** (0.073)</td>
<td>0.175*** (0.070)</td>
<td>0.258*** (0.086)</td>
<td>0.192*** (0.045)</td>
<td>0.456*** (0.101)</td>
<td>0.283** (0.118)</td>
<td>0.378* (0.217)</td>
<td>0.237*** (0.071)</td>
</tr>
<tr>
<td>(Federal Purchases/GDP)×Intensity</td>
<td>-23.72 (14.71)</td>
<td>-27.47*** (11.77)</td>
<td>-58.28*** (15.35)</td>
<td>-7.05 (16.74)</td>
<td>-14.20 (10.03)</td>
<td>-13.60 (27.64)</td>
<td>6.157 (14.97)</td>
<td>27.16 (64.17)</td>
<td>-31.03 (12.40)</td>
</tr>
<tr>
<td>(Forecasted Federal Purchases/GDP)×Intensity</td>
<td>32.61*** (6.27)</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

Firm and Time Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
Observations | 136,742 | 136,742 | 136,742 | 73,822 | 136,742 | 134,544 | 133,465 | 112,123 |
Number of Firms | 5,624 | 5,624 | 5,624 | 3,189 | 5,624 | 5,537 | 5,489 | 3,817 |

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.

Columns 1 and 2: Use alternative stock-price volatility measures
Columns 3 and 4: Add controls for future government purchases (interacted)
Columns 5 and 6: Use variants on main firm-level exposure measure
Columns 7 and 8: Use alternative firm-level exposure measures
Column 9: Restrict attention to larger firms
How Large Are the Estimated Effects of EPU on the Cross Section of Stock-Price Volatility?

Example: Overall U.S. EPU rose by 86 log points from 2006 to 2012, and Financial Regulation and Healthcare EPU indices rose by even larger amounts.

Estimated effects on option-implied firm-level stock price volatility in selected industries:

- Ordnance: +4.6 log points
- Healthcare: +13.9
- Heavy Construction: +0.6
- Aircraft, Parts: +3.3
- Engineering Serv.: +3.3 points
- Finance: +23.8

- Contrast to July-Aug. 2001 to Sep.-Oct 2001 (before and after 9-11) episode
Similar approach to firm-level panel regressions for investment rates (I/K) and employment growth rates

Next Slide: Sample period runs from 1985 to 2012. All specs include a full set of firm and time effects. I/K is the investment rate defined as CapEx_t/(Net Plant, Property and Equipment)_{t-1}. ΔEmp is the employment growth rate measured as (emp_t - emp_{t-1})/ (0.5×emp_t + 0.5×emp_{t-1}), and ΔRev is the corresponding revenue growth rate. Δ(Federal Purchases/GDP)×Intensity is the change in (Federal Purchases/GDP) from NIPA tables in the next quarter in quarterly specifications and in the next year in annual specifications, multiplied by firm-level policy exposure intensity variable. Δ(Forecast Federal Purchases/GDP)×Intensity instead uses the mean forecasted change in (Federal Purchases/GDP), drawing on NIPA data for current values and forecast data for future values. 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.
Firm-Level Panel Regressions for (I/K) and Employment Growth Rates

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

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>(1) I/K</th>
<th>(2) I/K</th>
<th>(3) I/K</th>
<th>(4) I/K</th>
<th>ΔEmp</th>
<th>ΔEmp</th>
<th>ΔEmp</th>
<th>ΔEmp</th>
<th>ΔEmp</th>
<th>ΔRev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(EPU)×Intensity</td>
<td>-0.032*** (0.010)</td>
<td>-0.032*** (0.010)</td>
<td>-0.024** (0.011)</td>
<td>-0.031*** (0.010)</td>
<td>-0.213** (0.084)</td>
<td>-0.227** (0.089)</td>
<td>-0.220** (0.118)</td>
<td>-0.207** (0.084)</td>
<td>-0.128</td>
<td></td>
</tr>
<tr>
<td>Δ(Federal Purchases/ GDP)×Intensity</td>
<td>8.20*** (2.86)</td>
<td>8.04*** (2.86)</td>
<td>12.12*** (3.18)</td>
<td>8.23*** (2.87)</td>
<td>10.79 (7.41)</td>
<td>15.60*** (8.04)</td>
<td>3.19 (12.56)</td>
<td>11.58 (7.58)</td>
<td>20.39*** (9.43)</td>
<td></td>
</tr>
<tr>
<td>Δ(Forecasted Federal Purchases/GDP)×Intensity</td>
<td>1.01 (0.828)</td>
<td>0.094</td>
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<td>-4.65*** (2.89)</td>
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<tr>
<td>Defense EPU × Defense Firm</td>
<td>0.094 (0.314)</td>
<td>(1.60)</td>
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<tr>
<td>Healthcare EPU × Health Firm</td>
<td>-0.422* (0.231)</td>
<td>1.16 (1.42)</td>
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<tr>
<td>Financial Regulation EPU × Finance Firm</td>
<td>-0.270*** (0.076)</td>
<td>0.636* (0.353)</td>
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<td></td>
</tr>
</tbody>
</table>

Periodicity
- Quarterly
- Yearly

3 Years Fed Exp leads
- No
- Yes

Observations
- 709,120
- 411,832
- 162,006
- 108,718
- 162,006
- 151,653

Number of Firms
- 22,358
- 22,358
- 14,190
- 22,358
- 17,151
- 13,018
- 17,151
- 15,929

Full set of firm and time effects in all columns
Columns 1 and 5: Basic specs for (I/K) and employment growth, respectively
Columns 2 and 6: Adding controls for future government purchases (interacted)
Columns 3 and 7: Using average (G/Y) during next 12 quarters (interacted)
Columns 4 and 8: Adding category-specific EPU measures
Column (9): Using revenue growth rate as dependent variable and basic spec
These results imply sizable investment and large employment effects in sectors with heavy exposure to government spending

Consider EPU increase from 2006 to 2012 (85.6 log points) for firm with government policy exposure intensity of 0.25.

- The estimated one-time drop in the quarterly investment rate implied by Column (2) is $(85.6)(.25)(-.032) = -0.68$ percentage points, which is about one-sixth as large as the median quarterly investment rate of 4.2 percentage points.

- Similarly, the estimated annual employment growth rate effect implied by Column (7) is $(85.6)(.25)(-.22) = -4.7$ percentage points.

- Unlike the implied volatility specifications, the investment rate and employment growth specs are changes regressed on changes. Thus, the investment and employment results are estimated one-time effects.
Summary of Firm-Level Regression Results

• High EPU raises firm-level stock-price volatility in sectors with heavy reliance on government spending (e.g., healthcare, defense-related industries, infrastructure investments) and high exposure to regulation (e.g., healthcare, financial services).

• Rising EPU lowers firm-level investment rate and employment growth in sectors with heavy reliance on government spending and high exposure to regulation.

• These effects on firm-level stock-price volatility, investment rates, and employment growth rates are sizable in sectors with high exposure to policy.
9. Short Tour of Related Indices, Methods, Text Sources and New Survey Instruments
Related Text-Based Indicators

1. Azzmonti (2016): Same method to get index of Partisan Conflict Intensity. Notable similarities and differences between PCI and EPU. Main difference: EPU rises but PCI falls in response to national security concerns, e.g., 9-11 attack.

2. Hassan et al. (2016): Uses earnings call conference transcripts as text source. Instead of human audit, uses text of Accounting and Political Science textbooks to separate policy from non-policy terms. Their national and category-specific EPU indices exhibit a lot of similarity to ours.
Related Text-Based Indicators

3. Mueller and Rauh (2016): Uses LDA topic models to develop geopolitical risk indices for many countries. Claims their indices have better predictive power of violent conflict than other indicators. Note: They hired many RAs to download many thousands of full-text articles from Lexis-Nexis.

4. We are currently working to develop a suite of news-based equity market uncertainty indices.

5. We are currently working to much more intensively exploit SEC filings to construct firm-specific EPU indices.
New Surveys of Business Expectations and Uncertainty

1. Federal Reserve Bank of Atlanta Business Decision Maker Survey
U.S. Business Decision Maker Survey

- National firm-level panel with about 1,200 participants currently. We continue to expand the panel.
- Operated by Atlanta Fed and co-branded with Stanford and the Chicago Booth School of Business.
- Nick Bloom and I have been working with Mike Bryan, Nick Parker and Brent Meyer at the Atlanta Fed over the past three years to develop, field test and refine the survey instrument and build out the sample.
- Very short questionnaire that takes 5-8 minutes. We aim for CEO or CFO respondents.
- The survey elicits 5-point subjective probability distributions over future shipments, capital expenditures, employees, and unit costs. Two versions of the survey instrument, with a two-month rotation cycle. Random allocation of survey units to rotation groups.
- We get monthly response rates >40%.
- We hope to issue some first results in early 2017.
Decision Maker Survey

In partnership with Steven Davis of the University of Chicago Booth School of Business and Nicholas Bloom of Stanford University, the Federal Reserve Bank of Atlanta has created the Decision Maker Survey. The only survey of its kind, the Decision Maker Survey measures firms' year-ahead expectations and associated uncertainties regarding changes in their costs, prices, profit margins, level of employment, capital investment, and sales revenue. The survey panel consists of a national sample of firms representing every sector of the economy (with the exception of agriculture and government) and a broad range of firm sizes.

Please note that due to the ongoing growth of the Decision Maker Panel, the sample size and sector composition of the panel vary significantly from month to month. These results are instructive but not representative of overall economic conditions.

Year-ahead Expectations and Uncertainty

Average Price Change

Average Unit Cost

Source: Federal Reserve Bank of Atlanta Decision Maker Survey
A typical question: here asking about sales one year from now

Projecting ahead over the next twelve months, please provide the approximate percentage change in your firm's SALES LEVELS for:

• The LOWEST CASE change in my firm’s sales levels would be: ____%
• The LOW CASE change in my firm’s sales levels would be: ____%
• The MEDIUM CASE change in my firm’s sales levels would be: ____%
• The HIGH CASE change in my firm’s sales levels would be: ____%
• The HIGHEST CASE change in my firm’s sales levels would be: ____%
Followed up by asking the probabilities of these sales outcomes

Please assign a percentage likelihood to these SALES LEVEL changes you selected above (values should sum to 100%)

• ___% : The approximate likelihood of realizing the LOWEST CASE change
• ___% : The approximate likelihood of realizing the LOW CASE change
• ___% : The approximate likelihood of realizing the MEDIUM CASE change
• ___% : The approximate likelihood of realizing the HIGH CASE change
• ___% : The approximate likelihood of realizing the HIGHEST CASE change
U.K. Business Decision Maker Survey

- Special question example:

Decision Maker Panel

6. Could you say how the UK's decision to vote 'leave' in the EU referendum is likely over the next year. What is the percentage likelihood (probability) that it will:

- Have a large POSITIVE influence on sales, adding 5% or more to revenue
- Have a minor POSITIVE influence on sales, adding less than 5% to revenue
- Have no material impact on sales
- Have a minor NEGATIVE influence on sales, subtracting less than 5% from revenue
- Have a large NEGATIVE influence on sales, subtracting 5% or more from revenue

Total
Coming soon….MOPS 2015….generously funded by Kauffman, NSF, Sloan Foundation & the Census
MOPS 2015 adds new questions on uncertainty & expectations of manufacturing plant managers

MOPS = Management & Organization Practices Survey, a stratified random sample of about 40,000 U.S. manufacturing plants. MOPS is fielded as a supplement to the Annual Survey of Manufactures, and it is fully linkable to the ASM, the Census of Manufactures and other sources of survey data and administrative records housed at Census Bureau.

MOPS 2015 went to the field in 2016. It includes questions about actual outcomes in 2015 and anticipated outcomes in 2016. The uncertainty portion of the MOPS also includes questions that elicit 5-point subjective probability distributions over future shipments, capital expenditures, employees, and materials costs in 2017. The next slide shows an example.

30 For calendar years 2015 and 2016, what are the approximate dollar values of **products shipped**, including interplant transfers, exports and other receipts at this establishment? Exclude freight charges and excise taxes.

For 2015 calendar year

<table>
<thead>
<tr>
<th></th>
<th>$Bil.</th>
<th>Mil.</th>
<th>Thou.</th>
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</table>

Estimate for 2016 calendar year

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<tr>
<th></th>
<th>$Bil.</th>
<th>Mil.</th>
<th>Thou.</th>
</tr>
</thead>
</table>

31 Looking ahead to the 2017 calendar year, what is the approximate dollar value of **products shipped** you would anticipate for this establishment in the following scenarios, and what likelihood do you assign to each scenario?

<table>
<thead>
<tr>
<th>2017 scenarios, from lowest to highest</th>
<th>Approximate dollar value of shipments in 2017</th>
<th>Percentage likelihood (values in this column should sum to 100)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Bil.</td>
<td>Mil.</td>
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<tr>
<td>LOWEST</td>
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<td>LOW</td>
<td></td>
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<tr>
<td>MEDIUM</td>
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<td>HIGH</td>
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<tr>
<td>HIGHEST</td>
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</table>

<table>
<thead>
<tr>
<th>Total</th>
<th>100</th>
<th>%</th>
</tr>
</thead>
</table>


Additional Slides
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 6: U.S. EPU Compared to 30-Day VIX, January 1990 to July 2015

Corr(VIX, EPU Index) = 0.58

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

Correlation of number of policy-triggered jumps per year with EPU index is 0.78

- Non-Policy increases
- Policy increases
- Policy decreases
- Non-Policy decreases

Based on human readings of next-day news articles
About large S&P Index moves in the New York Times
And the Wall Street Journal. Jump threshold: +/- 2.5%

Reproduced from “What Triggers Large Stock Market Jumps?” by Scott Baker, Nick Bloom & Steven Davis
Figure 5: Federal Tax Code Expirations Index, 1991-2013

Undiscounted projected 10-year revenue impact of scheduled tax code expirations:
- Before 2003 < $250 billion
- 2009-2012: $3-5 trillion

2013: Huge drop due to "Fiscal Cliff" resolution

Notes: Based on Congressional Budget Office data on projected revenue effects of federal tax code provisions set to expire in the current calendar year and next ten years. For a given year, the index value is calculated as the discounted sum of projected revenue effects associated with expiring tax code provisions, using a discount factor of $0.5^T$ applied to future revenue effects for $T=0,1,...,10$ years. Index normalized to a mean of 100 before 2010. This chart is reproduced from earlier drafts of Baker, Bloom and Davis (2015).