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The power of print: Uncertainty shocks, markets, and the economy

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ABSTRACT

There has been, in recent years, a renewed interest in and a growing recognition of the role played by uncertainty shocks in driving fluctuations in the economy and in asset markets. We create new text-based indicators of both general economic and policy specific uncertainty from New York Times and use them first, to chart changes in the level of uncertainty in the US for the period 1985–2007, second, to determine the role of policy in these swings, and, third to assess their impact on the economy, equity markets, and business cycles. Overall, our results indicate that uncertainty shocks – both general and policy related – depress the level of economic activity, significantly increase stock market volatility, and decrease market returns.

1 . Introduction

The Great Recession has led to a resurgence of interest in the effects of uncertainty shocks on the economy and the stock market. Empirical attempts to answer the questions, 'What happens to economic activity following an uncertainty shock?' and 'How important are these shocks in explaining business cycles?' have, for the most part, relied on interest rate spreads, stock market volatility, and disagreement among professional forecasters to measure changes in uncertainty.[1] In a pair of articles, Alexopoulos and Cohen (2008, 2009) proposed a new general economic uncertainty (*GEU*) measure based on counts of economic uncertainty articles in the New York Times. This approach has since been embraced and expanded in a variety of ways by a number of economists—most notably by Baker, Bloom, and Davis (2013), (here in referred to as BBD), whose economic policy uncertainty (EPU) index is primarily derived from a newspaper-based metric. In this paper, we present an expanded and refined version of the news-based uncertainty measures and use them, first, to identify fluctuations in the levels of general economic and policy related uncertainty in the US for the period 1985–2007,[2] second, to determine the role played by these measures of uncertainty in driving business cycles, and, third, to assess their impact on the economy and the stock market. Overall, our results indicate that uncertainty shocks – both general and policy related – depress the level of economic activity, significantly increase stock market volatility and decrease market returns.

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[1] See for example, Bernanke (1983), Romer (1990), Bachmann, Elstner, and Sims (2013), and Bloom (2009).

[2] The exclusion of the Great Recession years allows us to investigate the role of uncertainty shocks in explaining typical business cycles. The end date, on the other hand, was dictated by the lack of copyright permission to perform the analysis on NYT articles after 2007.

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Our findings contribute to two strands of literature. The first strand focuses on the economic effects of uncertainty and stems from Bernanke's (1983) seminal article on uncertainty and investment in which he argued that uncertainty shocks were likely to cause investors to postpone their capital expenditures. Our results are, on the whole, consistent with this argument and with the general predictions of theoretical models presented in Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) and Fajgelbaum, Schaal, and Taschereau-Dumouchel (2014) — namely that uncertainty shocks can cause sharp economic downturns. Moreover, our results complement the related empirical findings in Bloom (2009), Bachmann et al. (2013) and Jurado, Ludvison, and Ng (2013), even though these studies make use of different measures of uncertainty. The second, more recent strand, instead, deals with the effects of policy uncertainty. Here, our findings are consistent with those reported in both theoretical papers such as those of Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2011) and Pastor and Veronesi (2012) and in the empirical work of BBD (2013), Brogaard and Detzel (2012) and Julio and Yook (2012), where it is shown that a jump in economic policy uncertainty negatively impacts economic activity and causes stock market volatility to rise.

The creation of the enhanced news-based measures of uncertainty presented in this paper was motivated by three considerations. First, as confirmed by the behavior of Wall Street firms, there is important information that can be extracted from the media to help inform and understand trading decisions.[3] Second, the paper of Fajgelbaum et al. (2014) suggests that traditional measures of uncertainty, such as those based on volatility or ex-ante forecast error, may be inaccurate if uncertainty is endogenous. Finally, as demonstrated in Alexopoulos and Cohen (2008, 2009), uncertainty shocks, identified through changes in the number of New York Times' articles that contained the keywords (economic, economy or economies) AND (uncertain, uncertainties or uncertainty) seem to be important drivers of fluctuations in investment, employment, productivity and overall business activity.

While promising, reliance on such a limited number of keywords can raise questions about the sensitivity of the findings to the choice of language, in particular did they bias the results and if so, how? To address these questions, we first refined and expanded our original indicators of general economic uncertainty through a detailed textual analysis of all articles in the archives of the New York Times, and second, we created a corresponding set of economic policy uncertainty indices to assess the importance of this subgroup of shocks. Access to the complete text of all articles enabled us to work with a much larger set of uncertainty terms, and an extensive range of economic, financial, political, and business language to ensure that we have captured all articles of interest. Moreover, we are able to detect differences in the indices' composition (i.e., what fraction of articles refer to military issues, politics, elections, fiscal or legislation policy, monetary policy and foreign events), and clarify the sources of uncertainty through an examination of language in the vicinity of the terms and phrases associated with uncertainty.

We proceed as follows in the paper. In the second section, we discuss the creation and the properties of our new indicators and compare them to the VXO (the uncertainty measure used by Bloom (2009) and many others) and to BBD's blended *EPU* indicator. We find, in general, that jumps in uncertainty as measured by our newly created indicators are closely related to identifiable sources of unease about the economy. In the third, we use the indicators in a series of VARs to evaluate the macroeconomic impact of general and policy-related uncertainty shocks. Overall, we find evidence that both types have negative effects on output, investment, employment, and productivity. While the estimated magnitude of the impact varies with the indicator and the variables included in the regressions, they are consistently significant. For example, it is estimated that a major shock such as that associated with 9/11 would decrease output by 0.5–2.3%, employment by 0.4–1.1%, investment by 1.8–5.4% and productivity by approximately 1%. In the fourth section, we focus sharply on the effect of general and policy related uncertainty on stock market returns and stock market volatility. In keeping with the finance literature, we present results from a series of GARCH and E-GARCH models. We find the following: first, increased uncertainty decreases returns on the S&P 500; second, the introduction of uncertainty indicators to the models pushes up estimated volatility; third the standard ARCH and GARCH effects often lose significance with the introduction of the uncertainty indicator into the model. In the fifth and final section, we conclude with suggestions for future research.

2. The indicators

The motivation to develop news-based indicators of uncertainty stems from the inherent shortcomings associated with traditional measures.[4] For example, while stock price volatility may reflect fluctuations in uncertainty, it may also be a response to changes in leverage, tolerance for risk, or even sentiment. Indicators based on cross-sectional dispersion in productivity, profits and sales may fluctuate over the business cycle because of cyclical features of a firm's business and may, therefore, have nothing to do with uncertainty. Similarly, differences among forecasters may reflect nothing more than differences in opinion about the future, perfectly consistent with a rational expectations model and totally unrelated to uncertainty.[5] Text-based uncertainty indicators, on the other hand, have a number of attractive features. They are consistent over time and place and offer a broad coverage in terms of potential sources of uncertainty. Moreover, because a textual analysis provides a clear indication of the source of the uncertainty, its use permits us to identify different types of uncertainty and potentially different impacts. As explained in the Introduction, the enhanced indicators adopted in this paper, while motivated by the same considerations, represent a significant improvement in the scope and reliability of the first generation indicators.

The intuition behind news-based indicators is compelling. Newspaper publishers, to attract and maintain their readership (and to make profits), have an incentive to report on issues of wide spread interest in a timely manner. Since readers are interested in events

[3] See e.g., the newspaper article by Sarfraz Manzoor published 23 July, 2013 in the Telegraph available at http://www.telegraph.co.uk/finance/10188335/Quants-the-maths-geniuses-running-Wall-Street.html, discussing how Wall Street is utilizing textual analysis.

[4] See Jurado et al. (2013) for a more complete overview of the issues linked to the various traditional indicators and the work by Fajgelbaum et al. (2014).

[5] See e.g., Diether, Malloy, and Scherbina (2002) and Mankiw, Reis, and Wolfers (2003).

that may impact their economic wellbeing, newspapers will optimally choose to report on them. As such, changes in government programs, taxes, regulation, unanticipated political turmoil, terrorist attacks, financial crisis, and so on, will cause the number of articles that deal with these issues to rise, and, if the effects of these events on the economy are uncertain, articles containing language on both the economy AND uncertainty should also increase. Trends in the number of these articles over time will, therefore, provide a good measure of swings in uncertainty as perceived by the general public.

2.1. Textual analysis

When devising an automated textual search, a number of factors must be considered. The first and perhaps most important is keyword or n-gram choice — what words or phrases represent uncertainty, capture economic issues, and should thus be included in the word list? Second, since many words have multiple meanings, especially in English, and these meanings often change over time, it is vital that the words or phrases are chosen so that the articles returned use the terminology in the proper context. Third, spacing and punctuation can confound computer searches – a computer, unless otherwise programmed, will read G.D.P. and GDP as two different words – the language lists must take this into account.

While the results based on simple keyword indicators provide evidence of the usefulness of the approach, there is good reason to believe, based on the observations in the previous paragraph, that it is possible to enhance the accuracy and reliability of text-based indicators through the use of expanded language lists and more sophisticated textual analysis. As we illustrate below, our enhanced measures do appear to offer a more complete picture of fluctuations in economic and policy uncertainty.

2.2. Creating the indicators

The three new indicators of general economic uncertainty and three new economic policy uncertainty indicators are based on an analysis of approximately 1.55 million news articles from Proquest's historical archive of the New York Times (NYT) from January 1985 to the end of 2007. The start date for our analysis was selected because it coincides with that of BBD (2013), thus facilitating comparison between our results and theirs. The end date, on the other hand, was dictated by the lack of copyright permission to perform the analysis on NYT articles after that date. The time period is brief enough to ensure relatively little change in the usage of language, while the absence of data post 2007 eliminates the possibility that the results are driven largely by the extraordinary uncertainty shocks associated with the Great Recession.

The NYT is used to create the indices for a number of reasons. First, it is the unofficial national newspaper of record for the U.S., and as such, has a wide readership (print and online) across a broad spectrum of the population. Further, as the Alliance for Audit Media's Audience Snapshot Database suggests, its digital subscriptions are the largest in the country with over a million subscribers and its website is one of the most popular online. Second, while USA Today and the Wall Street Journal have higher print circulation numbers (in part due to their hotel subscriptions), Alexopoulos and Cohen (2008, 2009) provide evidence that there is substantial correlation between the materials covered by the NYT and other major newspapers.[6] As such, indices based on the NYT should provide a good proxy for economic uncertainty covered by the news media in the U.S.

To minimize errors related to word omission (and OCR errors), and thus to increase the probability that we are drawing on all relevant articles when creating the indices, we have expanded the list of words and phrases used to identify articles related to both uncertainty and economic issues. Although the n-gram selection process did require some judgment calls, it was informed by an analysis of word use in a variety of sources. For example, we read over 6000 articles in the NYT for guidance, we consulted a number of thesauruses for synonyms, and we checked word lists compiled by linguists. This was followed by a series of saliency and textual neighborhood analyses on the returned articles to identify additional words and phrases. A sampling of these articles then ensured that the terms and phrases were actually on topic. Specifically, we began by calculating the frequency of the appearance of all terms per article across the entire NYT collection to develop an estimate of the number of times a given term would appear in a “representative article”. Next, we selected a word (or phrase) from our initial list and then repeated the word frequency analysis on this subset of articles to identify those terms that appeared more often than we would have expected based on the frequency of their occurrence in the whole corpus. This exercise allowed us first to pick up a number of words that were excluded from our original list but were clearly candidates for inclusion in a broader list and, second, to flag terms that were not obviously related to economics and thus required some modification of the search word(s) to ensure the returned articles contained economic content.

To help refine the language lists further, we then examined blocks of text that contained the search word(s) to see how the term was used in context. We replaced words that seemed to have multiple (often non-economic) meanings in English with multi-word phrases or other nearness restrictions to minimize errors of inclusion.[7] Our resulting expanded uncertainty list contains in excess of 500 common terms and phrases such as ‘unable to predict’, ‘unsure’, and ‘do not know’ that one usually associates with uncertainty and our expanded economic list consists of 11,725 economic — finance terms and partial phrases.[8]

[6] It is likely that TV coverage of the events also increases during turbulent economic times. See e.g., Doms and Morin (2004).

[7] For example, single, high yield words such as stock(s) and price(s) – which may be related to stock car racing or the ‘price of fame’ – were replaced with multi-gram phrases such as stock market(s) and stock price(s) while words such as supply were saddled with implementation rules such as “only include occurrences of supply if supply within 3 words of demand”.

[8] It should be noted the uncertainty list will capture over 500 phrases and the expanded economics list will identify more than 11,725 due to the inclusion of proximity conditions and partial phrases (e.g., “not certain” or “*'t certain”).

2.2.1. The general economic uncertainty indicators

We utilize three general economic uncertainty (*GEU*) indicators in our analysis. Our first, *GEU1*, is the baseline indicator ('basic economic-basic uncertainty') which is identical to the one presented in our early work. Specifically it is a simple count of all articles that contain at least one of the basic economic terms (economic, economy, or economics) AND one of the basic uncertainty terms (uncertain, uncertainty, or uncertainties). Articles included in our second index ('basic economic-extended uncertainty'), *GEU2*, must have one of the basic economic language terms AND any one of the 500+ terms found in the expanded uncertainty list. A comparison between the second index and the baseline case reveals the extent to which an expansion in the uncertainty language affects the number and timing of high uncertainty periods. The third index (the 'extended economic-extended uncertainty' index), *GEU3*, enumerates articles that contain at least one of the words or phrases in our extended uncertainty list AND that have at least 1.5% of text related to the extended economic language set.[9] This measure filters articles differently than the other two in that it captures a broader mix of economic, business, and financial articles but excludes those where only passing reference to economic uncertainty occurs — an article about an increase in divorce rates as a result of a jump in economic uncertainty would not make the cut.[10] This index may well do a better job than the others in isolating those articles that are of interest to Wall Street and thus help identify uncertainty shocks likely to have a larger effect on the stock market.

2.2.2. The economic policy uncertainty indicators

The *EPU* indicators are based on a subset of *GEU* articles that contain, in addition to the necessary economic and uncertainty language, one or more of the following terms: 'congress', 'deficit', 'federal reserve', 'legislation', 'regulation' or 'white house' (including related terms like 'regulatory' or 'the fed'). These policy terms are the same as those used by BBD (2013) to create their index and were selected through a detailed analysis of the policy language in their newspaper database. To maximize the comparability between our results and theirs, we adopt their choice of policy uncertainty language in the creation of our *EPU* indicators. Moreover, since their index also blends in a measure of disagreements among professional forecasters and information about tax expiration dates, a comparison of our baseline indicator with theirs should highlight differences caused by the inclusion of this additional information.

Our baseline *EPU* indicator ('basic economic-basic uncertainty-policy'), *EPU1*, is created from the subset of articles that contain basic economic and uncertainty language AND at least one occurrence of BBD's policy language. It should closely resemble the two-thirds of BBD's index based on newspaper articles — the only difference between the two is that we rely on NYT articles while they draw on wider assortment of newspapers. Our second indicator ('basic economic-extended uncertainty-policy'), *EPU2*, is augmented by the inclusion of articles with expanded uncertainty language, while our third ('extended economic-extended uncertainty-policy'), *EPU3*, includes articles with both expanded uncertainty and economic language.

As BBD (2013) point out, these indicators, by construction, are designed to capture more than *EPU* narrowly defined. They should also pick up uncertainty about *who* will make the decisions, *what* (*if any*) policy actions will be undertaken, and *when* they will occur. They should, in addition, measure the economic *effect*s of past, present and future policy actions and the uncertainty induced by policy *inaction*. Finally, the index should track economic uncertainty related to national security concerns. Below we present more evidence on the composition of *EPU* indices to help us better understand what is captured in them, and to highlight differences between them and the *GEU* indicators.

2.3. The properties of the indicators

Fig. 1 displays each of our article counts (normalized by the number days in the month) along with BBD's blended index and the stock market volatility measure used by Bloom (2009) based on the VXO.[11] Standard unit root tests suggest that all series are stationary around a trend. As expected, the number of articles used to create the *GEU* and *EPU* indices significantly increase as terms are added to the uncertainty and economic lists — even though those based on the extended economics list must also meet the 1.5% content threshold rule.

The figure also reveals a number of notable properties of the indicators. First, uncertainty appears to increase during recessions, but not all spikes in the uncertainty index coincide with recession dates (a pattern also seen in the volatility measure). This suggests that the indices do indeed pick up more than the negative sentiment of agents during bad economic times. Second, while there is a relatively high correlation between the different indices, it is clear that they are not perfect substitutes for one another. The correlation between our *GEU* indicators and those of BBD ranges from 0.42 to 0.62, while the correlations between our new *EPU* indicators and BBD's are between 0.39 and 0.57. In both cases, the highest correlation with BBD is associated with the 'basic economic-extended uncertainty' measure, *GEU2*. The correlations between the baseline 'basic economic-basic uncertainty', *GEU1*, and the other indices reveal a high correlation between it and the *GEU2* and *EPU2* indicators both of which use 'basic economic-extended uncertainty'

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[9] The choice of 1.5% as the cut-off rule was based on an analysis of approximately 25,000 front page articles. The economic content ratios were calculated for each, and then various aspects of the articles – title, basic economic language, etc. – were reviewed to see if the ratio rankings coincided with the economic content of the article. We also discovered that 1.5% appeared to be a natural inflection point — below it and the article's main topic was frequently not about economics, above it and it was.

[10] See Appendix A for some examples of articles that are contained in *GEU3* but would be missed by *GEU1* and *GEU2*, and articles that would be included in *GEU1* and *GEU2*, but not *GEU3*.

[11] While it is possible to normalize by the number of articles in the newspaper, we found, when reviewing the data, that while there was a significant decline in the total number of articles over the period, this was not true for the subset of articles tied to economics and business. As such, normalizing by the number of articles (the method used by BBD to detrend their newspaper series) would induce a sizable upwards bias. As a result, we prefer to normalize by the number of days in the month and include time trends in our regressions.

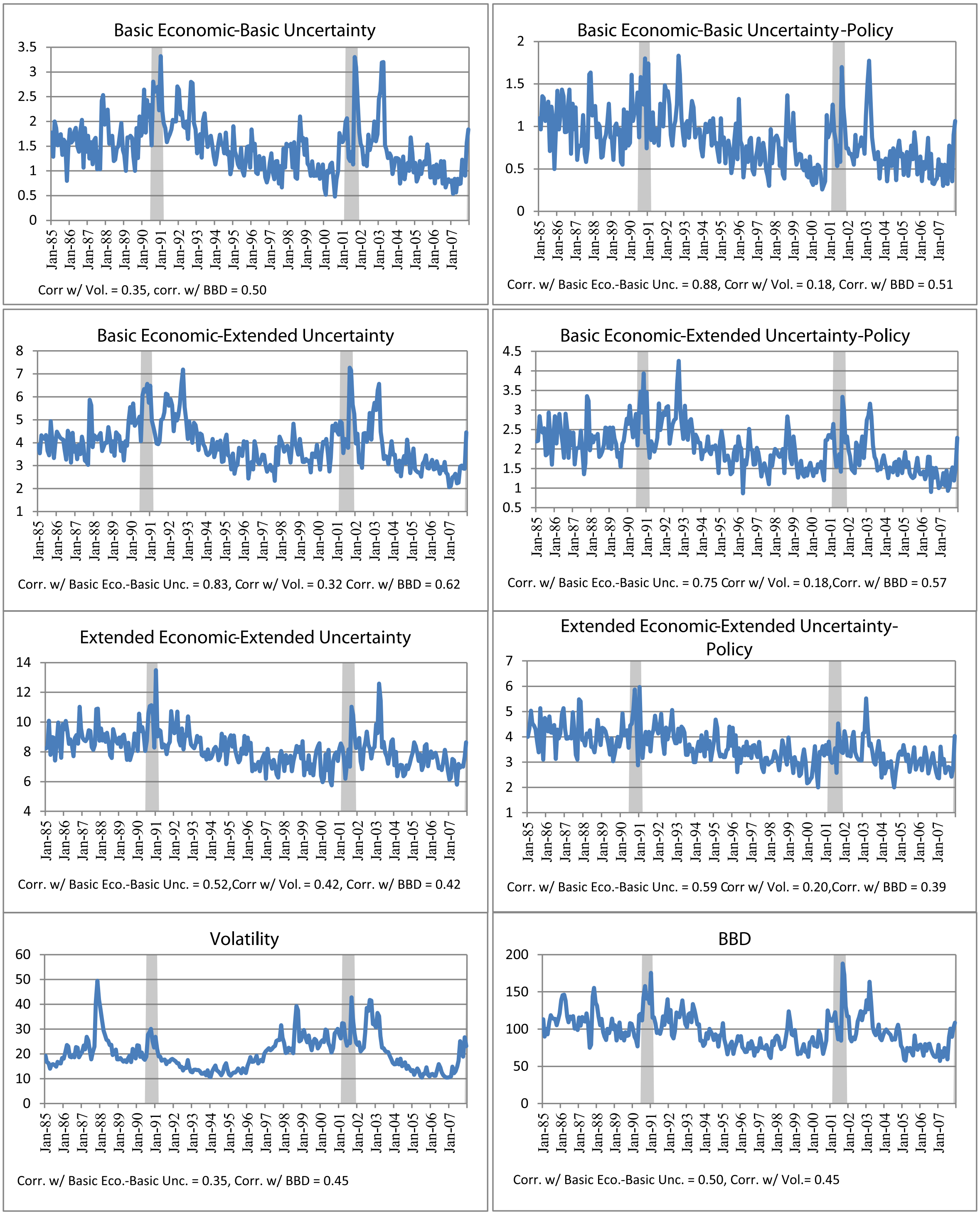


Fig. 1. The indicators. Note: Shaded areas are NBER Contractions. Each panel also displays three correlations — the correlation between the depicted index and (1) stock market volatility, (2) the BBD index, and (3) the baseline 'basic economic-basic uncertainty' index.

(0.83 and 0.75 respectively). On the other hand, much less correlation exists between the baseline indicator, *GEU1*, and *GEU3* and *EPU3* — the ones based on the set of articles whose primary focus, determined by the threshold rule, is economic/business in nature (0.52 and 0.59 respectively).

Our measures also display similarities with the volatility measure of uncertainty. However, as the figures show, the correlations between our new indicators and the stock market volatility measure tend to be lower than the correlation of the news-based indicators and BBD. In particular, the correlations with volatility range from 0.18 to 0.45, with the BBD index and the indicator most sharply focused on business and economic uncertainty, 'extended economic-extended uncertainty' displaying the highest correlations. Next, to more formally investigate the dynamic relationship between the VXO uncertainty index and each of our news-based indices, we estimated a series of bivariate VAR with 2 lags.[12] Overall, we found evidence that the VXO was Granger-caused by the uncertainty indices, but the reverse causality was seen only in the cases of the *GEU1*, *GEU2*, and BBD indices. Whenever the uncertainty indices were ordered first, and the uncertainty shock was identified using a Cholesky decomposition, we found evidence that volatility significantly increased in response to the shock.

Despite differences in the construction of the indicators, it is reassuring that they not only agree on the timing of upswings in uncertainty, but also that the jumps can be linked to real world events that we would expect to raise the level of uncertainty. Overall, we see large spikes occur around the time of Black Monday, Gulf War I (uncertainty starts to rise with the invasion of Kuwait), the election of Bill Clinton, the Asian–Russian Crises (and Long Term Capital Management's troubles), the Bush–Gore Election, 9/11 and Gulf War II. Uncertainty also appears to be on the rise at the very end of our period, a first intimation of trouble in the credit market. While some of these dates are closely associated with domestic policy changes – the election of a new president – others, such as 9/11, are times where the initial uncertainty did not come from the policy arena.

2.4. Exploring differences in the indices' composition

A more detailed analysis of the articles used in the various *GEU* and *EPU* indices helps highlight the differences between them. Therefore, to determine their composition, we created seven additional language lists linked to: domestic monetary policy, fiscal/government spending, legislation, elections, domestic and foreign geographic markers, and the military. The first contains 299 terms and phrases including those related to Federal Reserve activities and the names of all members of the FOMC during years 1985–2007. The second is composed of more than 1900 terms and phrases linked to taxes, military spending, housing and benefit programs, welfare, federal and state aid, the federal budget (including surpluses and deficits), and other fiscal expenditures. The names of specific programs are included (e.g., aid to families with dependent children) as are generic terms such as federal spending. In similar fashion, the legislative list (over 2000 words and phrases) includes both general terms – regulation, veto the bill, legislation – and the names of major pieces of legislation. Election/Voting is made up of 1050 general terms including losing/gaining seats, polling, approval ratings, balloting, voting, whistle-stops, and political campaigns. Finally, the geographic lists are comprised of references to major cities and places inside and outside the US, and the military list contains over 300 terms linked to attacks, weaponry, casualties and death counts, invasions, wars and terrorism.

To facilitate automatic content analysis, we used the word lists to identify those articles with at least 1% of their language related to one of military, fiscal, legislative, voting/election, and monetary policy. We also had the computer single out articles with substantial foreign content where we defined substantial to mean articles with at least 10 geographic markers AND where either (a) a minimum 1% of their total content was linked to the foreign geographic list[13] or (b) 47.5% of all their geographic references were foreign.[14] Tables 1 and 2 report the average values for the indicators and a breakdown of the statistics for various periods associated with heightened uncertainty.[15] As a brief summary, we find for the basic economic case, approximately 40% of the articles contain substantial foreign content, while for the expanded uncertainty language, it is 24% — suggesting this index is more focused on domestic issue. Many articles have a significant political slant, although, as one might expect, political considerations are most prominent in the *EPU* indicators.

The statistics also indicate that the composition of the indicators shift in response to the source of the shock. For example, the role of elections/voting, legislative, and, more generally, political language rises as a fraction of the total around midterm and presidential election dates. As the statistics for the sub-periods in Tables 1 and 2 show, at the time of Gulf War I, 9/11, and Gulf War II, the fraction of language tied to military/terrorism, foreign place, and government expenditures (the Fiscal category) went up substantially relative to mean values. The period of the Russian financial crisis and Long Term Capital Management (LTCM) failure led to an increase in references to both monetary issues and foreign locales. In addition, there is a rise in the contribution of political language to our indicators in the July–December 1992 period, legislative concerns jump, a normal consequence of the uncertainty associated with the outcome of the presidential election and its implications for policy. Black Monday and its aftermath scores high on fiscal/financial issues[16] while the beginning of the Credit Crunch (2007) seems to be primarily linked to monetary policy concerns.

A fine-grained textual analysis also permits us to address two fundamental questions about the sources of fluctuations in our *GEU* and *EPU* indicators. First, are the fluctuations in *GEU* driven by economic uncertainty or are they, instead, simply capturing aspects of policy uncertainty and, second, does *EPU* really reflect pure policy uncertainty or is it, instead, merely capturing general economic uncertainty that attracts the attention of policy makers? An examination of the language immediately surrounding the uncertainty terms in a set of our indicators helps us answer these questions.[17] As can be seen in Fig. 2 (based on the basic economic-extended

[12] Two lags were included based on the results of the AIC and BIC criteria. The VARs also included a constant, monthly dummy variables and a quadratic time trend.

[13] While we did not use the ratios for purposes beyond the breakdown presented here, the thresholds of 1% for the subcategories and 1.5% for the general political category were chosen by applying the same method used to select the 1.5% threshold discussed earlier.

[14] We chose a number slightly below 50% because often the words 'New York' would appear in phrasing linked to the newspaper (e.g., special correspondent to the New York Times).

[15] A set of graphs depicting the breakdowns of the indicators for all dates are contained in Appendix C.

[16] Just prior to the crash the Ways and Means Committee of the U.S. House of Representatives filed legislation to eliminate tax benefits associated with financing mergers. Carlson (2007) points out that this event, which happened on the Wednesday before the crash, may have been one of the contributing factors to the decline in the stock market.

[17] 'Immediately surrounding' refers to terms found within 20 words of the uncertainty language. This 20-word window was chosen because it represents a rough approximation of the length of sentences in New York Times articles and thus ensures that the terms are either in the same sentence or in adjacent ones.

Table 1
Peak date compositions — general economic uncertainty indicators.

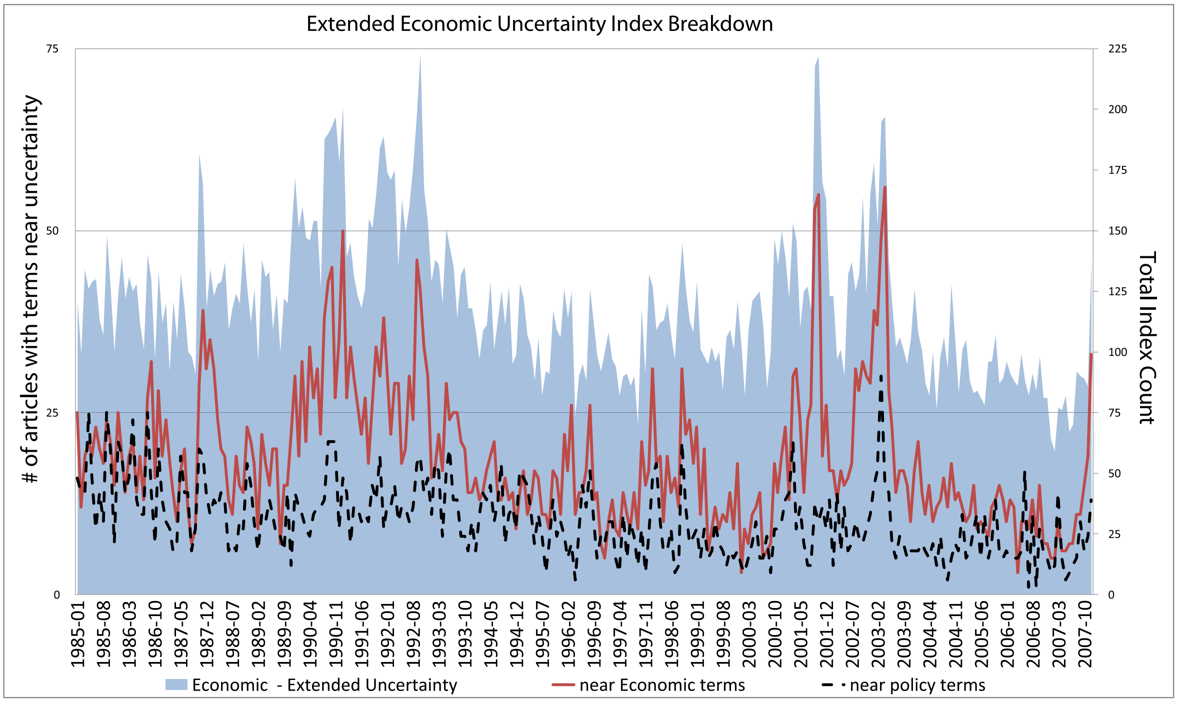
Content indicator	Total period	1987:10–1988:03	1990:07–1991:05	1991:06–1992:06	1992:07–1992:12	1998:07–1999:03	2001:09–2002:03	2002:12–2003:06	2007:07–2007:12
Basic economic-basic uncertainty									
Foreign	0.42	0.86	1.12	1.17	1.04	1.22	0.63	0.90	0.89
Political	0.64	1.00	1.03	1.06	1.10	0.96	0.69	0.91	0.84
Fiscal	0.24	1.21	1.33	1.01	1.16	0.97	0.82	1.35	0.56
Legislative	0.10	0.71	0.77	1.25	1.35	0.75	0.45	0.64	1.17
Fiscal or leg.	0.30	1.15	1.19	1.05	1.24	0.91	0.73	1.14	0.75
Elections/voting	0.15	0.83	0.71	1.08	1.78	0.82	0.56	0.68	0.83
Monetary	0.07	0.77	0.78	0.69	0.96	1.14	0.49	1.06	1.50
Military	0.11	0.88	1.43	1.19	0.70	0.64	1.37	1.94	0.61
Basic economic-extended uncertainty									
Foreign	0.41	0.89	1.18	1.10	0.88	1.11	0.74	0.95	1.00
Political	0.60	1.08	1.06	1.09	1.12	0.93	0.81	0.92	0.83
Fiscal	0.19	1.35	1.40	1.02	1.05	0.90	0.78	1.31	0.67
Legislative	0.09	0.93	0.85	1.12	1.21	0.77	0.41	0.81	1.00
Fiscal or leg.	0.25	1.27	1.25	1.04	1.12	0.87	0.69	1.13	0.77
Elections/voting	0.16	1.03	0.73	1.13	1.95	0.90	0.65	0.72	0.91
Monetary	0.04	1.06	1.00	0.85	0.89	1.08	0.40	0.84	1.40
Military	0.12	1.06	1.53	1.10	0.73	0.74	1.45	1.79	0.67
Extended economic language-extended uncertainty									
Foreign	0.24	0.91	1.34	1.17	1.19	1.16	0.80	1.25	1.00
Political	0.54	1.08	1.11	1.09	1.10	0.91	0.84	1.03	0.83
Fiscal	0.21	1.18	1.40	1.04	1.06	0.86	0.79	1.35	0.71
Legislative	0.11	0.98	0.98	1.10	1.08	0.82	0.59	0.87	0.89
Fiscal or leg.	0.28	1.13	1.28	1.04	1.09	0.86	0.77	1.22	0.77
Elections/voting	0.12	0.90	0.83	1.04	1.65	0.93	0.64	0.74	0.94
Monetary	0.02	1.08	1.17	1.05	1.25	1.06	0.57	0.87	1.32
Military	0.10	0.95	1.64	1.02	0.94	0.86	1.52	2.13	0.88

Notes: Column (2) reports the average fraction of articles during the full sample period that were identified as having at least 1% of their language related to the military, fiscal, legislative, voting/election, or monetary policy lists or 1.5% tied to general political language. Columns (3)–(9) report the ratio of the fraction of the articles related to the groups in the sub-period to the average fraction for the entire period in Column (2). As a result, a statistic above 1 indicates a higher than average fraction of articles linked to that category. The date ranges fall around the following events: 1987 stock market crash (1987:10–1988:3), Gulf War1 + NBER contraction (1990:7–1991:05), jobless recovery + aftermath of Gulf War + economic issues in Europe (1991:06–1992:06), presidential election Bush vs. Clinton (1992:07–1992:12), Russian Crisis and LTCM failure (1998:07–1999:03), 9/11 (2001:09–2002:03), Gulf War 2 (2002:12–2003:06), and start of Credit Crunch (2007:7–2007:12).

Table 2
Peak date compositions — economic policy uncertainty indicators.

Content indicator	Total period	1987:10–1988:3	1990:7–1991:05	1991:06–1992:06	1992:07–1992:12	1998:07–1999:03	2001:09–2002:03	2002:12–2003:6	2007:7–2007:12
Basic economic-basic uncertainty-policy									
Foreign	0.39	1.00	1.18	1.11	1.11	1.32	0.71	0.96	0.85
Political	0.81	0.99	1.05	1.04	1.09	1.00	0.80	1.00	0.83
Fiscal	0.34	1.12	1.39	1.02	1.15	0.93	1.05	1.37	0.49
Legislative	0.14	0.76	0.83	1.27	1.19	0.74	0.54	0.75	1.17
Fiscal or leg.	0.42	1.10	1.24	1.06	1.20	0.87	0.93	1.18	0.69
Elections/voting	0.19	0.73	0.85	1.13	1.75	0.84	0.62	0.83	0.72
Monetary	0.12	0.76	0.86	0.79	0.93	1.10	0.61	1.21	1.64
Military	0.10	1.24	1.74	1.19	0.71	0.41	1.70	2.42	0.64
Basic economic-extended uncertainty-policy									
Foreign	0.37	0.93	1.21	1.12	0.93	1.24	0.75	0.98	0.95
Political	0.80	1.01	1.03	1.05	1.11	0.99	0.89	1.00	0.86
Fiscal	0.29	1.29	1.36	1.00	1.06	0.91	0.92	1.34	0.68
Legislative	0.15	0.88	0.88	1.11	1.04	0.82	0.49	0.91	0.99
Fiscal or leg.	0.38	1.20	1.23	1.03	1.09	0.88	0.81	1.17	0.77
Elections/voting	0.22	0.87	0.75	1.16	1.87	0.94	0.68	0.90	0.95
Monetary	0.08	1.01	1.06	0.88	0.86	1.10	0.48	0.92	1.52
Military	0.11	1.15	1.60	1.05	0.72	0.63	1.73	2.13	0.65
Extended economic-extended uncertainty-policy									
Foreign	0.24	0.92	1.26	1.17	1.24	1.35	0.78	1.14	1.04
Political	0.80	1.02	1.06	1.06	1.09	0.97	0.90	1.02	0.87
Fiscal	0.33	1.16	1.36	1.03	1.04	0.89	0.81	1.30	0.74
Legislative	0.21	0.93	0.98	1.10	0.98	0.84	0.62	0.92	0.95
Fiscal or leg.	0.44	1.09	1.23	1.03	1.06	0.87	0.78	1.17	0.80
Elections/voting	0.21	0.79	0.85	1.02	1.58	0.95	0.65	0.81	0.98
Monetary	0.05	1.07	1.18	1.02	1.19	1.11	0.61	0.91	1.49
Military	0.10	0.95	1.49	0.95	0.93	0.72	1.68	2.06	0.97

Notes: Column (2) reports the average fraction of articles during the full sample period that were identified as having at least 1% of their language related to the military, fiscal, legislative, voting/election, or monetary policy lists or 1.5% tied to general political language. Columns (3)–(9) report the ratio of the fraction of the articles related to the groups in the sub-period to the average fraction for the entire period in Column (2). As a result, a statistic above 1 indicates a higher than average fraction of articles linked to that category. The date ranges fall around the following events: 1987 stock market crash (1987:10–1988:3), Gulf War1 + NBER contraction (1990:7–1991:05), jobless recovery + aftermath of Gulf War + economic issues in Europe (1991:06–1992:06), presidential election Bush vs. Clinton (1992:07–1992:12), Russian Crisis and LTCM failure (1998:07–1999:03), 9/11 (2001:09–2002:03), Gulf War 2 (2002:12–2003:06), and start of Credit Crunch (2007:7–2007:12).



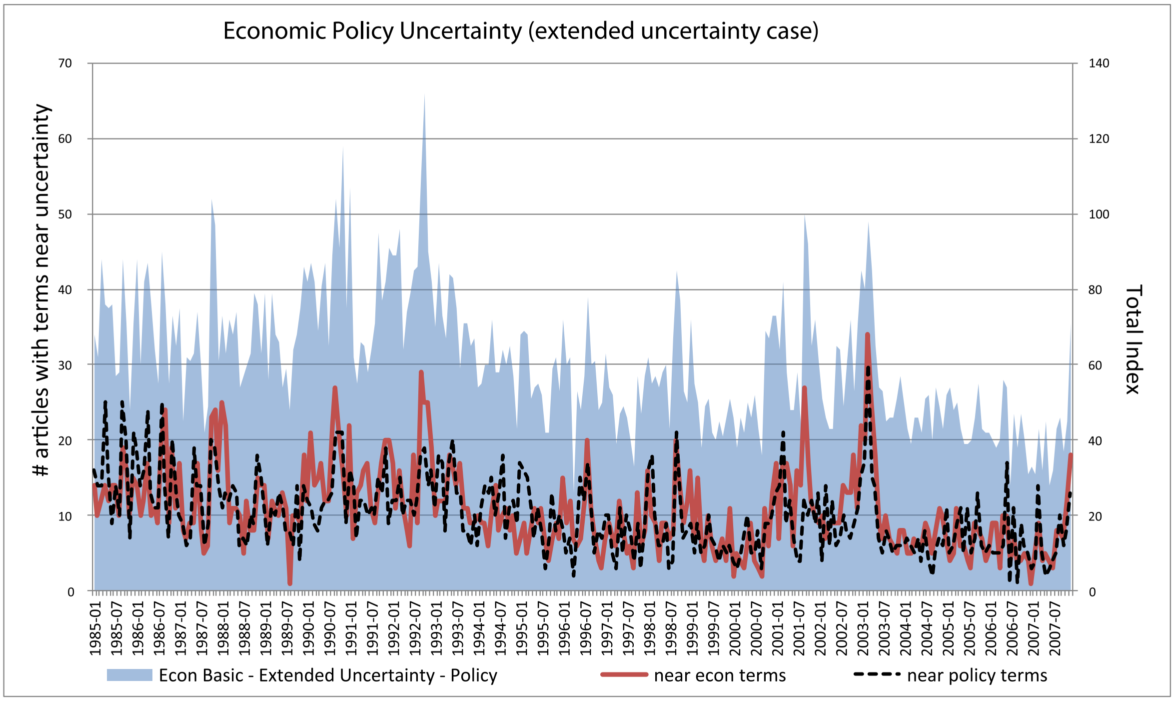


Fig. 2. Comparing the Indicators.

uncertainty lists for *GEU* and *EPU*), there are more articles with economic and uncertainty language appearing in close proximity in the *GEU* index than in the *EPU* case.[18] This occurs despite the fact that the basic economic list contains far fewer terms than does the policy one. Given that there are a relatively small number of articles where both policy and economic terms occurred within 20 words of the

[18] Here we present the results for the *GEU2* and *EPU2* indicators for two reasons. First, the use of the extended uncertainty list ensures we will examine language around a largest number of uncertainty references. Second, since the *GEU2* and *EPU2* do not require the articles to have at least 1.5% business or economic language, we do not bias the results in favor of finding more frequent references to economic uncertainty.

uncertainty language, the patterns would seem to suggest that the answer to question 1 is that the *GEU* fluctuations are primarily linked to economic uncertainty and are not driven exclusively by policy-related uncertainty. In answer to question 2, we find that fluctuations in the *EPU* index more often are powered by a combination of uncertainty about policy and the economy. Indeed the spikes in the indices on Black Friday and 9/11 appear to be linked to general economic uncertainty, as do the uncertainty increases seen in 2002 caused by the collapse of Enron and WorldCom. The Gulf Wars, the bailout of Long Term Capital Management, the Ohio bank holiday of 1985 (caused by the savings and loans crisis) on the other hand, appear to have been caused by a combination of general economic and policy uncertainty — with the last two examples being cases where the economic uncertainty led to policy responses.

3. The macroeconomic effects of uncertainty shocks

In the final analysis, while these swings in uncertainty (and our new measures of them) may have some intrinsic interest, it is desirable to determine the impact of these shocks on the economy and their contributions to business cycles. To get at these issues, we run a series of vector autoregressions and, in keeping with the literature, use a short run restriction to identify the shocks.

3.1. The economic data

In addition to our newly created indicators, we use a number of data series in our analysis. Specifically, we use Bloom's (2009) index, based largely on the VXO, to measure stock market volatility. Our data on output, employment, price, interest rate, consumption and investment come from the following sources. We drew on the Federal Reserve's FRED database for the industrial production index, the consumer price index (CPI: total goods), the federal funds rate, the monthly population, hours worked and employment. The Standard and Poor's 500 index came from the Basic Economics Database (formerly known as Citibase) and the quarterly investment data (converted to a monthly frequency using the DISTR function in RATS) were drawn from the Bureau of Economic Analysis' website. Finally, similar to Carlino, DeFina, and Sill (2001) and Horvath and Verbrugge (1996), we created measures of monthly labor productivity (output per hour), measured by total industrial production divided by total hours.

3.2. The bivariate VARs

To begin our analysis, we considered the following bivariate VARs:

$$X_t = \alpha + \sum_{i=1}^{6} \mathrm{P}_i X_{t-1} + f(t) + u_t$$

where α is a vector of monthly dummy variables (to remove monthly trends), $X_t = [\ln(\text{uncertainty measure}_t), \ln(Y_t)]'$ and Y_t is one of the following at time t: industrial production, employment, investment, or labor productivity. A quadratic time trend, $f(t)$, is included to help capture changes in the number of articles in the New York Times over the time period. As in Alexopoulos and Cohen (2009), Bloom (2009) and BBD (2013) we use a Cholesky decomposition to identify the uncertainty shocks and, as such, we order our measures first, in keeping with the assumption that these shocks affect the other variable contemporaneously. We also include 6 lags to make comparisons between our results and those of BBD's (2013) as clean as possible.[19]

All of the indicators were found to Granger-cause the industrial production (*IP*) and employment variables with only the 'basic economic-extended uncertainty-policy' indicator granger causing *IP* at a 10% level. Investment and productivity did not Granger-cause any of the indicators, but investment was Granger-caused by the four indicators based on the extended uncertainty language. Productivity was Granger-caused by all indicators except the 'extended economic-extended uncertainty' and the 'basic economic-extended uncertainty' indicators — although the test statistic for the latter case fell just short of Granger-causing productivity at the 10% level.

The impulse responses of our variables to a one standard deviation uncertainty shock are reported in Fig. 3.[20] Dates marked with squares or dots are ones where the 90% confidence intervals indicate that the responses are significantly different from 0. Overall, an unanticipated increase in uncertainty leads to a drop in industrial production, investment, employment, and productivity — independent of the measure of uncertainty used.[21] The shocks, for the most part, translate into significant responses in the economy within a month and last between 36 and 48 months. Industrial production tends to decline for 12–18 months following a shock, while the maximum impact on employment is felt around the 20th month. In six of the seven cases, investment bottoms out by the third quarter — the exception is the case of 'basic economic-extended uncertainty' where the largest decrease is seen by the fifth quarter. Unlike the other variables, productivity responds to a shock after a delay of a few months, but the decrease remains significant for another 11–15 months. While there are some differences in magnitudes across the indicators, we generally find that the impact of a large shock such as that of 9/11, causes a roughly 2% drop in output and a 1% retreat in employment. Moreover, it causes investment

[19] The AIC and BIC criteria both tend to select a smaller number of lags. To determine the effects of lag choice on the results, we also ran a series of VAR with a smaller number of lags included. In general, we found that results in these cases suggested uncertainty shocks play a larger role in economic fluctuations.

[20] We also examined cases where the uncertainty indicators were ordered last, and cases where IP, employment, and productivity entered in first differences. These results also suggested that industrial production, employment, investment, and productivity fall in response to a shock that increases uncertainty.

[21] Gulen and Ion (2013) also find evidence, using BBD's measure of *EPU*, that an uncertainty shock causes corporate investment at the firm and industry levels to drop.

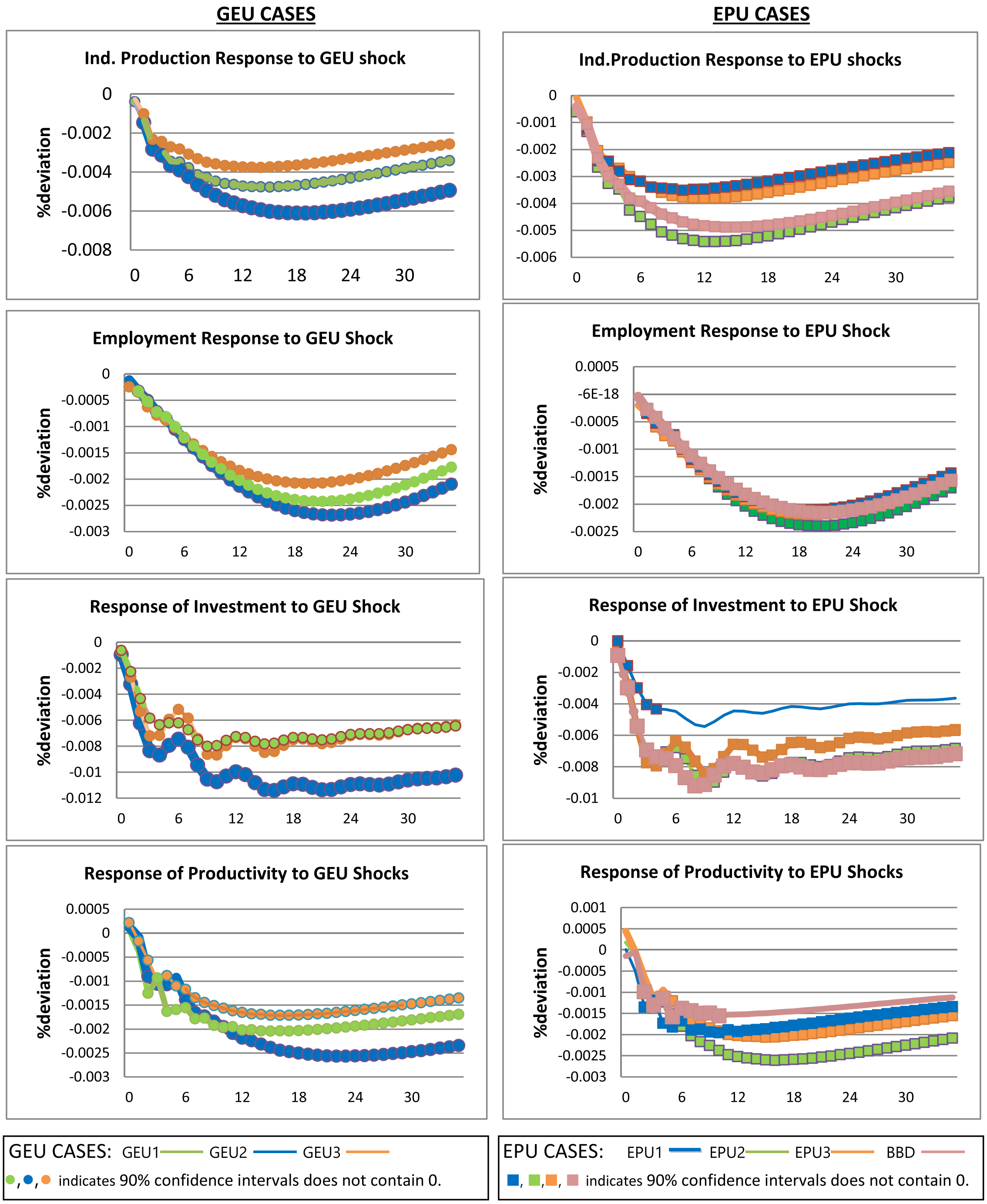


Fig. 3. Responses of macroeconomic variables to *GEU* and *EPU* shocks: bivariate VAR cases. Notes: The figures depict the response to a 1-standard deviation increase in uncertainty. Dots and squares indicate dates where the responses are statistically significant. *GEU1* is the basic economic-basic uncertainty case, *GEU2* is the basic economic-extended uncertainty case, *GEU3*, is the extended economic-extended uncertainty case, *EPU1* is the basic economic-basic uncertainty-policy case, *EPU2* is the basic economic-extended uncertainty-policy case, *EPU3* is the extended economic-extended uncertainty-policy case, and BBD is the Baker et al. (2013) blended EPU index. The bivariate VARs are estimated using data from 1985:1–2007:12 and include the ln(uncertainty index), a quadratic time trend, monthly dummy variables and one of the variables ln (*IP*), ln(Emp), ln(Inv) or ln(productivity). The uncertainty shock is identified using a Cholesky decomposition where uncertainty is ordered first.

declines of 1.9% to 5.4%, and productivity to fall about 1%. These are approximately the same magnitudes found by BBD (2013) following a similar sized *EPU* shock. Of our six indicators, the decreases predicted by the three *GEU*s slightly exceed those predicted by the *EPU*s. Finally, the largest impacts are observed for indicators based on the basic economic — extended uncertainty language, and/or BBD's blended index.

Table 3
Variance decomposition-bivariate case.

	GEU indicators						*EPU* indicators							
	IP			Employment			*IP*				Employment			
Horizon	[a]	[b]	[c]	[a]	[b]	[c]	[d]	[e]	[f]	[g]	[d]	[e]	[f]	[g]
1	0.65	0.84	0.26	0.95	0.88	4.18	0.46	1.62	0.04	0.79	0.42	0.36	2.87	0.14
	(0.0,3.5)	(0.0,4)	(0.0,2.5)	(0.0,4.1)	(0.0,3.9)	(1.0,9.2)	(0.0,3)	(0.1,5)	(0.0,1.7)	(0.0,4)	(0.0,2.9)	(0.0,2.7)	(0.5,7.5)	(0.0,1.9)
6	18.16	23.45	11.86	13.92	14.85	15.36	13.30	22.85	12.21	18.67	12.24	12.85	15.04	12.16
	(7.5,32.1)	(11.5,37.7)	(3.9,23.8)	(4.8,26.3)	(5.6,28.0)	(5.7,28.6)	(4.6,25.7)	(11.3,36.7)	(4.1,24.4)	(8.0,32.5)	(3.9,24.5)	(3.8,24.6)	(5.8,27.5)	(3.4,24.1)
12	25.41	36.49	16.34	24.88	27.81	21.88	16.48	34.72	17.32	26.91	20.83	24.54	23.24	20.99
	(9.5,46.2)	(18.1,56.6)	(4.2,35.6)	(9.3,44.1)	(11.8,47.4)	(7.1,41.0)	(4.0,35.4)	(15.8,54.9)	(4.3,36.0)	(10.2,47.0)	(7.2,38.3)	(8.6,43.1)	(8.6,41.8)	(6.2,39.6)
24	32.63	52.01	20.67	35.61	42.74	27.97	18.19	43.69	21.37	34.63	27.23	34.81	30.16	29.25
	(9.0,61.3)	(23.8,76.5)	(3.3,48.3)	(13.0,61.3)	(16.8,68.6)	(7.3,54.0)	(3.1,42.9)	(17.2,70.4)	(3.8,47.0)	(10.0,62.4)	(8.9,50.0)	(12.2,60.1)	(10.1,54.8)	(7.5,54.9)
36	35.35	58.84	22.26	39.92	49.44	30.44	18.64	46.41	22.60	37.69	29.49	38.64	32.80	32.70
	(8.5,67.5)	(26.1,83.7)	(3.1,53.9)	(13.9,67.8)	(18.8,77.1)	(7.4,58.6)	(2.8,45.4)	(17.5,74.4)	(3.6,50.1)	(9.1,68.7)	(9.5,54.1)	(13.1,66.2)	(10.4,58.9)	(7.7,62.2)
	Investment			Productivity			Investment				Productivity			
Horizon	[a]	[b]	[c]	[a]	[b]	[c]	[d]	[e]	[f]	[g]	[d]	[e]	[f]	[g]
1	1.84	4.25	2.53	0.02	0.06	0.16	0.79	3.40	2.22	4.06	0.00	0.09	0.63	0.07
	(0.1,5.7)	(1.1,9.4)	(0.3,6.8)	(0.0,1.8)	(0.0,1.7)	(0.0,2.3)	(0.0,3.7)	(0.6,8.1)	(0.2,6.2)	(0.9,9.5)	(0.0,1.5)	(0.0,1.9)	(0.0,3.2)	(0.0,1.9)
6	8.25	15.93	10.53	6.35	3.41	2.73	3.90	12.33	12.43	11.77	8.04	5.20	3.70	5.17
	(1.7,19.0)	(6.0,28.7)	(3.1,21.8)	(1.3,16.9)	(0.7,12.3)	(0.6,11.1)	(0.3,12.5)	(4.0,24.9)	(4.3,23.9)	(3.3,24.4)	(1.8,19.2)	(1.1,14.7)	(1.0,12.1)	(1.1,15.1)
12	14.01	25.21	15.30	11.33	9.97	6.47	6.53	18.84	16.11	18.98	12.63	15.12	10.01	7.84
	(2.7,32.1)	(9.7,43.8)	(3.9,34.1)	(1.5,29.6)	(1.5,26.2)	(0.7,21.8)	(0.6,21.7)	(5.5,38.4)	(4.5,34.1)	(5.2,38.3)	(2.0,31.1)	(3.4,33.4)	(1.4,27.1)	(1.0,23.8)
24	19.29	38.40	21.17	17.08	21.64	11.40	7.78	24.56	18.81	24.02	15.87	25.85	16.99	10.12
	(3.0,44.9)	(14.0,64.0)	(4.1,47.4)	(1.6,45.9)	(3.2,48.7)	(0.7,36.5)	(0.6,28.0)	(5.7,50.3)	(4.0,41.9)	(4.7,51.3)	(1.8,42.0)	(5.5,51.5)	(1.9,42.3)	(1.1,36.2)
36	21.30	44.61	23.28	19.65	28.35	13.58	8.18	26.52	19.72	26.18	16.88	29.80	19.56	11.04
	(2.8,50.6)	(15.9,73.4)	(4.2,52.3)	(1.7,53.9)	(3.8,60.4)	(0.7,43.6)	(0.6,30.1)	(5.7,54.7)	(3.8,44.4)	(4.5,58.0)	(1.6,45.8)	(6.3,58.2)	(2.1,47.9)	(1.1,41.5)

Notes: A column marked with an [a] indicates results from the bivariate model where the 'basic economic-basic uncertainty' index is used, [b] indicates the 'basic economic-extended uncertainty' case, [c] indicates the 'extended economic-extended uncertainty' case, [d] indicates the basic economic-basic uncertainty-policy case, [e] indicates the basic economic-extended uncertainty-policy case, [f] indicates the extended economic-extended uncertainty-policy case, and [g] indicates the Baker et al. (2013) EPU case. The bivariate VARs include the ln(uncertainty), the ln(variable), a quadratic time trend and monthly dummy variables. The shock is identified using a Cholesky decomposition where uncertainty is ordered first. The ranges in parenthesis give the 5th and 95th percentiles values for the variance decomposition based on Monte Carlo draws.

Table 3 reports the variance decompositions for the bivariate VARs along with 90% confidence intervals. As can be seen, the uncertainty indicators explain a sizable fraction of the variation, in the cases of *IP*, employment and investment — over 10% by the 6-month horizon with the effects continuing to grow over the 3-year horizon. For the three *GEU* indices, the maximum fraction of the variation in the first 3 years ranges from 23%–59% for *IP*, 30.4%–49.5% for employment, 21%–45% for investment, and 13.5%–28.5% for productivity For the *EPU* indicators, the maximums are, on the whole, slightly lower (*IP*, 18.6%–46.4%, employment, 29.5%–39%, and investment, 8.2%–26.5%) with the exception being productivity (16.9%–30%). The results using our basic economic-extended uncertainty policy indicator, *EPU2*, are similar to those based on the BBD index again with exception of productivity where the fraction of the variance attributable to the uncertainty captured by the BBD index was about 1/3 the size. In short, these results suggest that both *GEU* and *EPU* shocks may be important sources of fluctuations in industrial production, employment, investment, and productivity.

Finally, in most cases the news-based *GEU* indicators accounted for a larger share of the variance than those based solely on *EPU*. This may come as no surprise since, as indicated above, *EPU* could be thought of as a subset of general economic uncertainty. This is, in part, supported by data presented by BBD (2013). In an effort to uncover drivers of large jumps (2.5% or more) in the S&P 500 index during the period 1980–2007, they sought explanations in next day articles in the New York Times — 170 events in all. As it happens, broadly defined economic events were more often found to be the cause of the swings than policy-related ones — in fact only 14% were strictly linked to policy, whereas 31% had macroeconomic roots, 12% were tied to corporate earnings, 11% to war/terrorism, and 9% to interest rates.

Table 4
Variance decompositions: 6-variable multivariate VAR.

		Indicator						
	Horizon	[a]	[b]	[c]	[d]	[e]	[f]	[g]
Fed Funds	1	0.18	0.00	0.08	0.00	0.42	0.33	0.00
		(0.0,2.5)	(0.0,1.6)	(0.0,2.1)	(0.0,1.7)	(0.0,3.1)	(0.0,2.6)	(0.0,1.7)
	6	11.47	5.79	3.12	8.78	4.86	4.40	18.15
		(3.4,23.8)	(0.8,16.1)	(0.5,11.0)	(1.9,19.5)	(0.7,14.5)	(0.9,13.3)	(7.1,30.6)
	12	14.06	13.67	7.36	11.94	13.23	13.85	33.82
		(3.1,30.2)	(2.4,29.7)	(0.7,20.9)	(2.0,27.7)	(2.2,29.5)	(2.8,30.0)	(15.0,50.1)
	24	17.91	28.19	10.29	15.05	24.20	19.08	41.87
		(2.9,38.4)	(5.6,48.7)	(0.9,28.9)	(2.0,33.9)	(4.1,44.9)	(3.1,38.8)	(16.6,57.9)
	36	18.87	32.71	10.70	15.62	27.62	19.82	42.68
		(2.9,38.3)	(6.4,51.8)	(1.1,30.3)	(2.2,32.8)	(4.5,47.1)	(2.9,38.3)	(15.1,57.1)
Investment	1	0.66	2.27	1.47	0.36	1.46	1.06	2.74
		(0.0,3.9)	(0.2,6.9)	(0.0,5.0)	(0.0,3.1)	(0.1,5.5)	(0.0,4.7)	(0.3,7.2)
	6	4.48	11.90	7.96	3.87	11.44	10.50	12.96
		(0.4,14.5)	(3.3,24.7)	(1.5,18.5)	(0.3,13.0)	(3.1,23.8)	(2.7,21.9)	(3.7,24.9)
	12	8.48	23.44	8.12	7.73	23.28	11.73	22.82
		(1.2,23.4)	(8.0,40.0)	(1.7,21.7)	(0.9,22.4)	(7.1,40.9)	(2.5,26.3)	(8.0,39.3)
	24	7.22	24.41	4.09	5.79	23.29	6.70	15.23
		(1.0,23.9)	(6.2,45.2)	(1.5,16.8)	(0.8,21.7)	(5.4,44.1)	(1.8,21.6)	(4.1,33.7)
	36	4.91	17.91	3.60	3.89	17.24	4.91	10.17
		(1.1,21.5)	(4.5,40.0)	(1.4,16.1)	(0.9,17.9)	(3.9,38.1)	(1.8,17.4)	(3.5,28.0)
Employment	1	0.49	1.52	3.60	0.06	0.29	2.31	0.68
		(0.0,3.4)	(0.0,5.4)	(0.7,8.7)	(0.0,1.9)	(0.0,2.6)	(0.2,6.8)	(0.0,3.8)
	6	6.45	14.30	9.46	5.81	9.56	9.53	19.03
		(0.9,17.1)	(4.4,27.0)	(2.2,21.2)	(0.7,15.8)	(2.2,21.0)	(2.1,21.1)	(7.5,32.8)
	12	12.59	28.26	10.19	11.26	22.12	13.71	31.55
		(1.8,29.0)	(9.9,45.8)	(1.4,26.3)	(1.5,26.8)	(6.4,39.8)	(2.6,29.7)	(13.8,48.9)
	24	17.07	41.76	8.15	13.58	33.69	14.64	35.38
		(2.1,37.1)	(15.2,60.1)	(1.0,26.2)	(1.3,31.8)	(9.4,53.8)	(1.8,33.8)	(12.4,53.4)
	36	16.02	41.69	5.89	12.16	34.63	11.96	31.06
		(1.8,37.0)	(13.3,60.2)	(1.0,23.4)	(1.2,30.0)	(8.9,55.0)	(1.6,31.5)	(8.9,50.6)
Industrial production	1	0.35	1.70	0.09	0.30	1.81	0.03	1.06
		(0.0,3.0)	(0.1,5.6)	(0.0,2.1)	(0.0,2.7)	(0.1,5.9)	(0.0,1.8)	(0.0,4.2)
	6	8.78	22.18	4.29	8.57	20.12	7.71	20.08
		(2.0,20.8)	(10.0,35.1)	(0.7,13.4)	(1.8,19.6)	(8.5,33.8)	(1.5,18.2)	(8.6,33.4)
	12	10.57	32.12	3.38	9.83	29.26	8.23	25.08
		(1.5,27.1)	(13.4,48.7)	(0.6,14.6)	(1.3,25.3)	(11.0,47.3)	(1.2,22.4)	(8.9,42.9)
	24	11.07	36.12	1.99	8.88	31.59	6.17	21.47
		(1.2,30.6)	(12.4,55.4)	(0.6,14.8)	(1.0,26.7)	(8.9,52.0)	(1.0,22.6)	(5.2,41.1)
	36	9.51	32.06	1.47	7.22	28.24	4.50	17.22
		(1.0,29.1)	(8.7,53.8)	(0.6,14.6)	(0.9,25.2)	(6.4,50.5)	(0.9,20.7)	(4.0,38.6)

Notes: The columns correspond to the following indicators: [a] basic econ.-basic uncertainty, [b] basic econ.-ext. uncertainty, [c] ext. econ-ext. uncertainty, [d]basic econ.-basic uncertainty-policy, [e] basic econ.-ext. uncertainty-policy, [f] ext. econ-ext. uncertainty-policy, and [g] BBD. The multivariate VARs include, in the following order, the ln(uncertainty index), ln(S&P), Fed Funds rate, ln(Inv), ln(Emp) and ln (*IP*), a quadratic time trend and monthly dummy variables. The ranges in parenthesis give the 5th and 95th percentiles values for the Variance decomposition based on Monte Carlo draws.

Table 5
Variance decomposition: 8-variable multivariate VAR.

Horizon		Indicator								Indicator						
		[a]	[b]	[c]	[d]	[e]	[f]	[g]		[a]	[b]	[c]	[d]	[e]	[f]	[g]
1	Wages	0.41	0.29	0.06	0.19	0.44	0.65	1.00	Man. hours	1.11	1.31	0.43	1.31	2.71	0.63	0.33
		(0.0,2.9)	(0.0,2.6)	(0.0,2)	(0.0,2.5)	(0.0,3)	(0.0,3.9)	(0.0,4.5)		(0.0,4.8)	(0.0,5)	(0.0,3.2)	(0.0,5.1)	(0.3,7.1)	(0.0,3.4)	(0.0,2.8)
6		8.57	5.31	9.51	8.94	9.08	15.24	6.90		3.74	6.25	2.34	1.85	6.02	1.59	3.01
		(3.3,17.8)	(2.1,13.4)	(3.5,18.4)	(3.3,18.4)	(3.5,18.1)	(6.7,25.5)	(2.4,15.8)		(1.0,12.4)	(1.4,16.2)	(1.0,9.6)	(0.8,9)	(1.6,15.6)	(0.7,7.9)	(0.8,11.3)
12		8.43	6.59	11.00	8.54	9.50	13.87	7.36		3.67	5.61	3.07	2.32	5.48	2.82	3.92
		(3.6,17.9)	(2.9,16.0)	(4.4,20.7)	(3.5,18.7)	(4.0,19.2)	(6.4,23.9)	(2.8,17.6)		(1.8,12.5)	(2.3,15.6)	(1.7,11.0)	(1.4,10.5)	(2.3,15.0)	(1.6,10.9)	(1.7,13.3)
24		8.46	7.03	11.23	9.18	9.68	14.42	7.54		6.80	8.28	5.51	6.18	8.72	6.07	7.73
		(3.7,19.0)	(3.5,17.3)	(4.6,21.9)	(3.8,20.0)	(4.3,20.5)	(6.3,25.2)	(3.1,18.8)		(2.7,17.9)	(3.3,18.9)	(2.3,15.4)	(2.4,16.9)	(3.7,19.0)	(2.5,16.5)	(2.8,18.3)
36		9.13	7.76	11.55	9.98	10.43	14.86	8.82		7.18	8.99	5.38	6.51	9.61	6.16	8.88
		(3.9,21.2)	(3.7,18.9)	(4.5,22.3)	(3.9,21.4)	(4.4,21.9)	(6.3,26.0)	(3.4,21.8)		(2.7,19.5)	(3.5,20.8)	(2.4,15.9)	(2.5,18.2)	(3.9,21.4)	(2.7,17.5)	(3.0,21.0)
1	Fed Funds	0.72	0.39	0.01	0.19	0.05	0.03	0.29	Manufacturing emp.	0.00	0.41	0.36	0.04	0.04	0.31	1.30
		(0.0,3.4)	(0.0,2.8)	(0.0,1.9)	(0.0,2.6)	(0.0,2.2)	(0.0,1.8)	(0.0,3)		(0.0,1.8)	(0.0,2.9)	(0.0,3.2)	(0.0,1.8)	(0.0,1.8)	(0.0,2.9)	(0.0,4.7)
6		17.57	11.18	1.70	13.67	11.11	2.87	20.53		6.45	8.96	2.41	6.10	7.71	4.22	14.06
		(6.5,29.8)	(2.8,22.8)	(0.2,8.7)	(4.3,25.6)	(2.7,23.2)	(0.4,11.1)	(8.5,33.8)		(0.9,16.3)	(1.6,20.0)	(0.2,9.7)	(0.9,16.0)	(1.3,17.9)	(0.4,13.5)	(4.6,25.3)
12		19.63	17.10	2.53	17.09	20.24	8.66	32.99		5.95	8.58	1.15	5.16	9.09	2.68	14.65
		(5.2,35.4)	(3.8,33.2)	(0.3,13.4)	(3.9,32.9)	(5.0,36.3)	(0.9,23.2)	(13.7,48.1)		(0.8,18.8)	(1.2,22.1)	(0.4,8.6)	(0.8,17.2)	(1.3,23.6)	(0.5,13.2)	(3.3,28.8)
24		15.72	16.89	2.88	14.16	20.82	7.77	29.44		3.69	4.54	4.73	3.74	4.89	2.76	8.21
		(4.2,31.4)	(3.8,32.7)	(0.9,14.2)	(3.5,29.2)	(4.9,36.9)	(1.6,22.7)	(9.7,44.1)		(1.1,15.2)	(1.3,16.8)	(0.8,17.5)	(1.2,14.9)	(1.3,17.9)	(0.7,13.3)	(2.3,23.1)
36		16.58	15.69	5.79	15.61	18.89	10.28	26.54		7.56	6.47	8.60	7.96	6.66	6.68	9.21
		(4.5,31.1)	(4.0,30.7)	(1.2,18.4)	(4.3,28.8)	(5.1,33.5)	(2.3,24.0)	(8.9,40.2)		(1.5,22.6)	(1.6,21.8)	(1.0,22.4)	(1.5,22.3)	(1.6,20.7)	(1.2,21.0)	(2.6,24.5)
1	Prices	0.81	0.00	0.00	1.23	0.00	0.00	1.13	Industrial production	0.22	0.35	0.02	0.63	1.71	0.04	1.22
		(0.0,3.9)	(0.0,1.8)	(0.0,1.9)	(0.0,4.8)	(0.0,1.8)	(0.0,1.7)	(0.0,4.4)		(0.0,2.5)	(0.0,2.8)	(0.0,1.9)	(0.0,3.5)	(0.1,5.8)	(0.0,1.9)	(0.0,4.6)
6		7.28	2.47	5.48	4.05	1.99	4.03	1.49		2.48	3.65	0.50	3.45	5.30	2.44	7.69
		(1.7,18.2)	(0.5,10.7)	(1.4,14.3)	(0.9,13.7)	(0.5,9.8)	(1.3,12.4)	(0.6,9.2)		(0.6,10.4)	(0.6,12.0)	(0.4,5.4)	(0.6,11.9)	(0.8,15.5)	(0.5,9.9)	(1.2,18.1)
12		9.89	3.47	6.16	9.58	4.37	9.06	7.96		2.31	2.41	2.74	2.60	4.11	1.82	6.87
		(2.6,22.6)	(1.3,13.4)	(2.3,16.4)	(2.4,23.1)	(1.5,14.4)	(3.3,20.6)	(1.9,20.2)		(0.9,10.8)	(0.8,11.6)	(0.7,12.1)	(1.0,11.0)	(1.0,15.3)	(0.7,10.1)	(1.5,19.6)
24		12.44	7.04	7.24	12.47	9.20	11.99	13.40		7.36	4.58	9.46	8.41	5.55	7.06	7.13
		(3.2,27.6)	(2.0,20.8)	(2.5,19.6)	(2.9,27.3)	(2.3,23.5)	(3.8,25.1)	(2.8,28.6)		(1.4,21.2)	(1.2,16.9)	(1.6,23.0)	(1.8,21.5)	(1.7,17.6)	(1.5,19.6)	(2.3,19.8)
36		12.28	7.73	6.99	12.38	10.20	11.91	14.72		10.56	7.81	11.22	11.99	9.07	10.18	10.87
		(3.3,28.2)	(2.2,22.0)	(2.6,19.3)	(3.0,27.0)	(2.7,25.4)	(3.7,25.6)	(3.2,30.8)		(1.8,26.2)	(1.4,23.5)	(1.8,24.6)	(2.1,26.6)	(2.1,23.8)	(1.9,24.5)	(2.7,26.3)

Notes: The columns correspond to the following indicators: [a] basic econ.-basic uncertainty, [b] basic econ.-ext. uncertainty, [c] ext. econ-ext. uncertainty, [d] basic econ.-basic uncertainty-policy, [e] basic econ.-ext. uncertainty-policy, [f] ext. econ-ext. uncertainty-policy, and [g] BBD. The multivariate VARs include, in the following order, the, ln(S&P), ln(uncertainty index), Fed Funds rate, ln(wage), ln(CPI), ln(man. hours), ln(man.emp) and ln(*IP*). All data is H.P. Filtered. The uncertainty shock is identified using a Cholesky decomposition where the uncertainty index is ordered second. VARs are estimated on data from 1985:1–2007:12.

3.3. The multivariate cases

While the bivariate results are suggestive, it is reasonable to ask how sensitive they are to the inclusion of additional variables and/or the ordering of variables. To answer this question, we ran a series of multivariate VARs making use of the ordering assumptions and

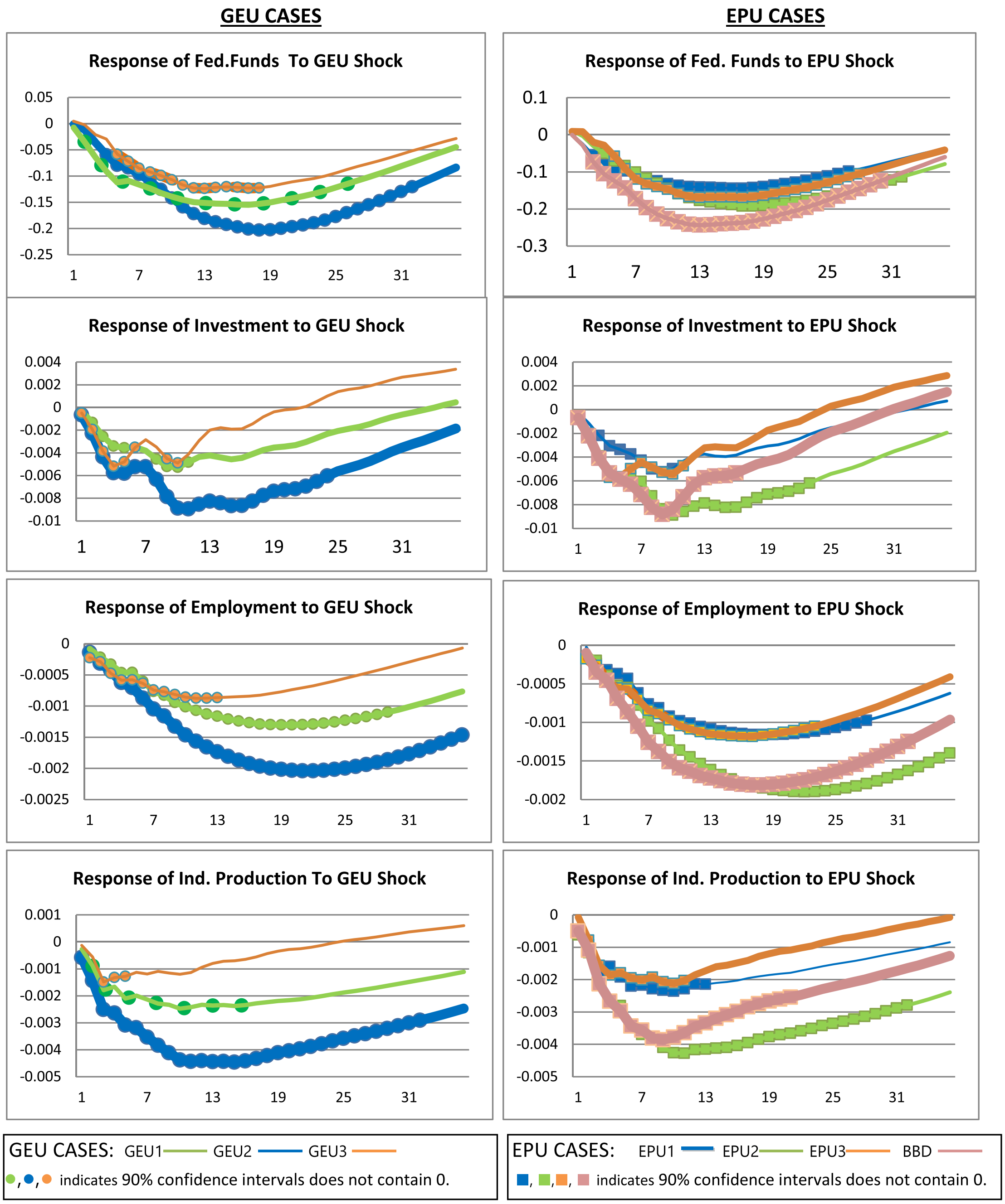


Fig. 4. Responses of macroeconomic variables to GEU and EPU shocks: 6-variable multivariate VAR cases. Notes: The figures depict the response to a 1-standard deviation increase in uncertainty. Dots and squares indicate dates where the responses are statistically significant. *GEU1* is the basic economic-basic uncertainty case, *GEU2* is the basic economic-extended uncertainty case, *GEU3*, is the extended economic-extended uncertainty case, *EPU1* is the basic economic-basic uncertainty-policy case, *EPU2* is the basic economic-extended uncertainty-policy case, EPU3 is the extended economic-extended uncertainty-policy case, and BBD is the Baker et al. (2013) blended EPU index. The multivariate VARs are estimated on data from 1985:1–2007:12 and include, in the following order, the ln(uncertainty index), ln(S&P), Fed Funds rate, ln(Inv), ln(Emp) and ln (*IP*), a quadratic time trend and monthly dummy variables. The uncertainty shock is identified using a Cholesky decomposition.

Fig. 5. Responses of macroeconomic variables to GEU and EPU shocks: 8-variable multivariate VAR cases. Notes: The figures depict the response to a 1-standard deviation increase in uncertainty. Dots and squares indicate dates where the responses are statistically significant. *GEU1* is the basic economic-basic uncertainty case, *GEU2* is the basic economic-extended uncertainty case, *GEU3*, is the extended economic-extended uncertainty case, *EPU1* is the basic economic-basic uncertainty-policy case, *EPU2* is the basic economic-extended uncertainty-policy case, *EPU3* is the extended economic-extended uncertainty-policy case, and BBD is the Baker et al. (2013) blended EPU index. The multivariate VARs are estimated on data from 1985:1–2007:12 and include, in the following order, the ln(S&P), ln(uncertainty index), Fed Funds rate, ln(wages), ln(Prices), ln(Manuf. Hrs), ln(Manuf. Emp) and ln(*IP*). As in Bloom (2009) and Jurado et al. (2013) the data in the VAR is H.P. filtered and the uncertainty shock is identified using a Cholesky decomposition.

detrending methods that have been commonly adopted in the literature. Specifically, we consider a series of six and eight variable VARs of the form:

$$X_t = \alpha + f(t) + \sum_{i=1}^{6} \beta_i X_{t-1} + u_t$$

In the six variable case, we again include a vector of monthly dummy variables, α, and the same time trend as in the bivariate case. In keeping with BBD's (2013) formulation, we order uncertainty first, and order the remaining variables as follows, $X_t = [\ln(\text{uncertainty}_t), \ln(\text{S\&P}_t), \text{Fed. Funds rate}_t, \ln(\text{investment}_t), \ln(\text{EMP}_t), \ln(IP_t)]'$. Our eight variable VAR instead follows Bloom (2009) and Jurado et al. (2013). As such, we eliminate the deterministic trend, adopt their ordering in which the stock market variable is placed first, and estimate the VARs using HP-filtered data. For this case, the variables enter in the following order: ln(S&P), ln(uncertainty index), Fed Funds rate, ln(wage), ln(CPI), ln(Manufacturing Hours), ln(Manufacturing Emp.) and ln(*IP*). The variance decompositions and impulse responses associated with these systems are presented in Tables 4 and 5 and Figs. 4 and 5.[22]

Although the impulse responses for the six variable cases seen in Fig. 4 are very similar to those for the bivariate ones, a few differences merit attention. First, the maximum impact on industrial production takes place about 2 months earlier in the multivariate case while the maximum impact on employment occurs approximately 6 months earlier (around months 16–18). The response of investment bottoms out at approximately the same horizon but returns to trend faster. These observations appear to be consistent across both *GEU* and *EPU* and correspond with the results based on the BBD index. These results indicate that a major shock the size of 9/11 would cause output to decline between 0.7% and 2.3%, employment 0.4% and 1.1%, and investment between 1.8% and 5.3%. Again, impacts are greatest for the basic economic-extended uncertainty, *GEU2*, and BBD's blended index.

The responses in Fig. 5, based on the eight variable cases (with the HP-filtered data), also show a decline in industrial production, manufacturing employment and hours worked immediately following the shock. However, the responses now tend to mimic the

[22] As an additional sensitivity analysis, we ran a 7 variable VAR that also included volatility. The impulse response functions from these regressions again suggest that uncertainty shocks can cause industrial production, employment, investment and the stock market to decline. There was also evidence that these shocks are often accompanied by a decline in the federal funds rate.

patterns reported in Bloom (2009) — namely, the variables fall sharply during the first one or two quarters and tend to overshoot pre-shock levels during recovery.[23] Moreover, a positive shock to uncertainty also leads to a decrease in wages, prices and the federal funds rate. For the majority of these cases, a shock similar to the size of 9/11 would cause industrial production to fall by 0.5–1%, manufacturing employment by 0.4%–0.9%, manufacturing hours by about 0.4%, wages by about 0.5% and prices by about 0.4%.

The variance decompositions for the six variable VARS are reported in Table 4. Even with the inclusion of the other variables, we still find that a sizable share of the variation is linked to economic and economic policy uncertainty. For the case of the three *GEU* indices, the maximum fraction of the variation in the first 3 years ranges from 4.7% to 36.6% for I.P., 10.2% to 43% for employment, 8.5% to 26.4% for investment, and 10.7% to 32.7% for the Federal Funds rate. For the *EPU* indices (including BBD), the maximum fraction of the variation in the first 3 years ranges from: 8.3% to 32.1% for I.P., 13.6% to 35.5% for employment, 7.7% to 25.2% for investment, and 15.7% to 43% for the Federal Funds rate. As with the bivariate regressions, we find that the fraction of the variation attributable to the basic economic-extended uncertainty indicators is larger than for indicators base on the basic economic-basic uncertainty language. The weakest results were linked to the indicators based on articles with a minimum 1.5% economic/business language. Finally, with the exception of the Federal Funds rate, the two versions of the basic economic- uncertainty indicator (*GEU2* and *EPU2*) explained a higher share of the variances than the BBD indicator did, especially at longer horizons.

The results in Table 5 present the variance decompositions associated with the 8-variable VARs. The fraction of the variation linked to *GEU* and *EPU* is found to be somewhat smaller, but not insignificant.[24] Specifically, the maximum fraction of the variation in *IP* in the first three years ranges from 7.8%–11.2% for the *GEU* cases, and 9.1%–12% for the *EPU* ones. For manufacturing employment they range from 7.6%–10.1% for *GEU* and 6.7%–15.8% for *EPU* and for manufacturing hours, 5.5%–9.1% and 6.3%–9.7%.[25] The wage and price findings are of similar magnitude with the lower end just below 8% and the upper end touching 15%.

In summary, both *GEU* and *EPU* shocks can cause sharp recessions — although their length and depth are sensitive to indicators used. Our findings also suggest that the uncertainty shocks can explain a non-negligible portion of the short-run fluctuations, despite the fact that we focus on the period of the Great Moderation, and thus exclude the recession of 1981 and, of course the Great Recession.[26]

4. The effects of uncertainty on the stock market

Our objective in this section is to explore the effects of *GEU* and *EPU* on the stock market. Since all our indices are monthly, we focus, by necessity, on the relationship between uncertainty, stock returns, and volatility at monthly frequencies. It is worth noting, as can be seen in the first panel of Fig. 6, that the monthly returns display quite a bit of randomness with some extreme outliers, with periods of relative calm (1993 to mid-1996, and early 2004 to mid 2007) and others with much greater volatility. Interestingly, the high variance periods occur during times of heighted uncertainty such as the market crash of October 1987, Gulf Wars 1 & 2, the 1990–91 recession, the Asian and Russian Crises, 9/11, the Dot-com bubble collapse, the failures of Worldcom and Enron, and the beginning of the Credit Crunch.[27] The prima facia evidence would then seem to suggest that uncertainty, stock market volatility, and, stock returns move hand in hand. [28]

Given that the swings in returns on the S&P 500 appear to be time-varying, we use our new indicators in a series of standard volatility models – namely Bollerslev's (1986) GARCH and Nelson's (1991) E-GARCH models – to investigate the relationship between uncertainty and the market.[29] We begin the analysis by testing to see if the log levels of the monthly returns contain a unit root and specifying a mean equation for a basic GARCH(1,1) with no uncertainty variables. The resulting baseline mean equation is:

$$r_t = \alpha + \beta r_{t-1} + \varepsilon_t$$

where

$$\varepsilon_t = \eta_t \sqrt{h_t}\,,\ \eta_t \sim iid(0,1)$$

andr_t is the first difference of the log of monthly returns. A set of monthly dummy variables is included and an AR(1) term is added in the mean equation based on the specification suggested using the standard AIC criterion. The standard Engel and McLeod–Li tests

[23] To determine if the overshoot behavior is a consequence of differences in detrending or in the variables included, we also ran an eight variable VAR where we included the deterministic trend (as before) but did not HP-filter the data. In this case, we found limited evidence of an overshoot.

[24] A set of eight variable VARs where the uncertainty term was ordered first was also examined. Although not reported here, the results are overall similar with the exception that when the uncertainty measures are ordered first, there is a noticeably larger fraction of employment variation linked to *GEU* and *EPU*.

[25] These are similar in magnitude to the results shown in Jurado et al. (2013) utilizing different uncertainty measures.

[26] For example, Jurado et al.'s (2013) measures suggest that the largest uncertainty shocks in the post 1960 period appear to occur around the 1981–82 recession and the Great Recession.

[27] While we focus on the S&P 500, there is evidence that increased economic uncertainty also affects other markets as well. See e.g., Ewing and Malik's (2013) work on the volatility of gold and oil futures.

[28] Kollias, Papadamou, and Stagiannis (2011) also provide evidence that terrorist attacks in Europe – which arguably increased uncertainty – affected volatility and market returns.

[29] While most GARCH models are estimated using daily data, Greasley, Madsen, and Les Oxley (2001) use monthly stock market data in a GARCH model to create a measure of uncertainty for the US economy, and McAleer, Chan, and Marinova (2007) apply a GARCH to monthly patent data.

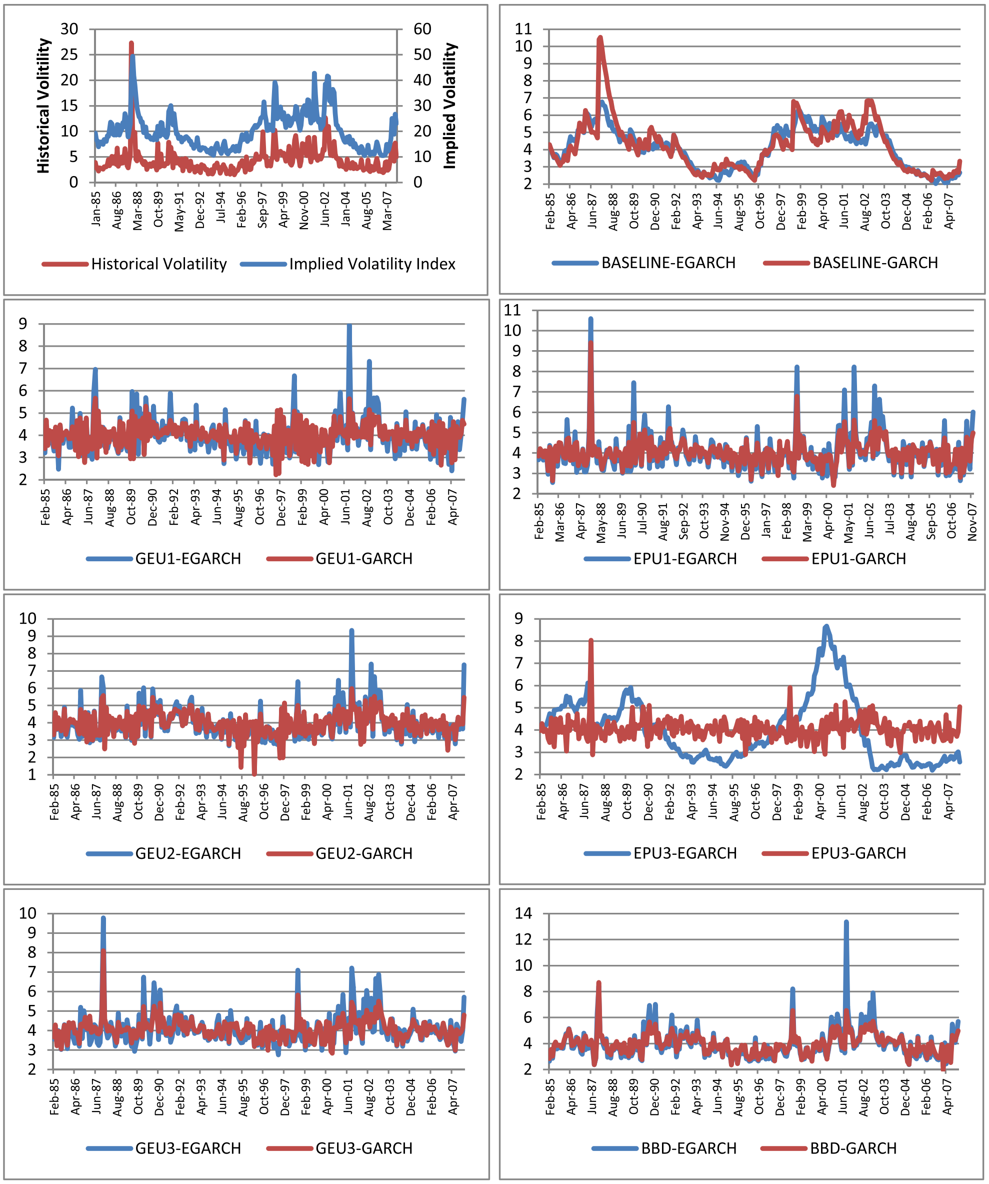


Fig. 6. Estimated volatility measures. Notes: Historical volatility is the standard deviation of monthly stock returns from daily returns in the month and implied volatility is based on the VXO. Baseline indicates the results of the GARCH(1,1) model and E-GARCH(1,1) without any uncertainty indicators included. *GEU1* indicates the use of the basic economic-basic uncertainty index, *GEU2* indicates the basic economic-extended uncertainty case, *GEU3* indicates the extended uncertainty-extended economic case, *EPU1* indicates the basic economic-basic uncertainty-policy case, EPU3 indicates the extended economic-extended uncertainty-policy case, and BBD indicators the Baker et al. (2013) EPU index case.

confirmed the presence of ARCH effects indicating a GARCH specification is appropriate. The variance equation for our basic GARCH(1,1) is given by:

$$h_t = \omega + \gamma\varepsilon_{t-1}^2 + \delta h_{t-1},$$

and the model was estimated using Maximum-Likelihood under the assumption that the errors are normally distributed. We then tested the standardized residuals post estimation to ensure that there was no evidence of serial correlation or ARCH effects at standard levels of significance to confirm the validity of the chosen specification. The estimated coefficients and robust standard errors are reported in the second column of Panel A in Table 6 and the estimated standard deviations from the baseline model are shown in Panel 2 of Fig. 6.

Table 6
GARCH and E-GARCH estimated for S&P 500 returns.

Mean equation	Baseline	*GEU1*	*GEU2*	*GEU3*	*EPU1*	*EPU3*	BBD
Panel A: AR(1)–GARCH(1,1)							
Constant	2.105***	2.154***	2.304**	2.077*	1.874*	2.211***	1.915*
	(0.784)	(0.909)	(0.907)	(1.197)	(1.065)	(0.791)	(1.057)
Returns($t-1$)	−0.044	−0.080	−0.083	−0.099	−0.113*	−0.114*	−0.122*
	(0.072)	(0.054)	(0.057)	(2.218)	(0.067)	(0.069)	(0.068)
Uncertainty	N/A	−2.185***	−3.601***	−4.153*	−2.162***	−3.927*	−3.021**
		(0.656)	(1.038)	(2.218)	(1.261)	(2.046)	(1.302)
Variance equation							
Constant	0.331	29.335***	27.040***	17.355**	19.293***	21.599***	18.871***
	(0.308)	(3.105)	(3.415)	(7.548)	(4.924)	(7.702)	(7.702)
a	0.138***	0.028	0.025	0.070	0.111	0.074	0.081
	(0.045)	(0.022)	(0.025)	(0.094)	(0.109)	(0.063)	(0.097)
b	0.858***	−0.819***	−0.690***	−0.101	−0.273	−0.373	−0.244
	(0.039)	(0.105)	(0.163)	(0.460)	(0.260)	(0.296)	(0.328)
Uncertainty	N/A	12.342***	28.268***	29.612***	11.562***	19.661*	30.533***
		(2.578)	(5.014)	(10.273)	(3.090)	(10.859)	(5.936)
Log-likelihood	−768.679	−769.693	−765.591	−774.511	−770.692	−773.4	−763.838
Panel B: AR(1)–E-Garch(1,1)							
Mean equation	Baseline	*GEU1*	*GEU2*	*GEU3*	*EPU1*	*EPU3*	BBD
Constant	2.059***	1.860*	2.103***	1.984***	1.745***	2.157***	1.751
	(0.441)	(1.004)	(0.501)	(0.528)	(0.487)	(0.644)	(0.009)
Returns($t-1$)	−0.027***	−0.075	−0.054	−0.087	−0.104	−0.042	−0.113
	(0.002)	(0.063)	(0.073)	0.089	(0.077)	(0.054)	(0.059)
Uncertainty	N/A	−2.116***	−3.547***	−2.902	−1.997***	−1.831***	−2.741
		(0.700)	(1.164)	(3.441)	(0.710)	(0.151)	(0.126)
Variance equation							
Constant	−0.127**	3.876***	3.973***	2.714***	2.991***	−0.084	3.255***
	(0.060)	(0.646)	(0.682)	(1.040)	(1.172)	(0.095)	(0.358)
a	0.190**	0.204	0.174*	0.088	0.252	0.142	0.190*
	(0.074)	(0.153)	(0.105)	(0.127)	(0.202)	(0.170)	(0.113)
b	0.992***	−0.482**	−0.521**	−0.003	−0.162	0.990***	−0.268**
	(0.022)	(0.222)	(0.255)	(0.370)	(0.403)	(0.021)	(0.119)
d	0.082	−0.082	−0.079	−0.204	−0.124	0.038	−0.073
	(0.054)	(0.103)	(0.084)	(0.125)	(0.123)	(0.078)	(0.083)
Uncertainty	N/A	1.130***	2.098***	2.053*	0.965**	−0.358***	2.647***
		(0.251)	(0.620)	(1.204)	(0.475)	(0.157)	(0.585)
Log likelihood	−763.332	−764.913	−762.048	−771.547	−767.167	−759.293	−759.494

Notes: All cases include monthly dummy variables in the mean equation. Results are based on S&P 500 monthly returns over the period 1985:1–2007:12. Numbers in parenthesis are robust standard errors. Uncertainty is the coefficient of the uncertainty indicator and Returns($t-1$) identify the coefficient on the lagged returns. ***, ** and * represent statistical significance levels at 1%, 5% and 10%, respectively.

Next, to explore the impact of uncertainty, we added the detrended uncertainty metrics to the baseline model in both the mean and variance equations.[30] The new equations took the following forms:

$$r_t = \alpha + \beta r_{t-1} + \lambda Unc_t + \varepsilon_t, \text{ and } h_t = \omega + a\varepsilon_{t-1}^2 + bh_{t-1} + \tau Unc_t$$

Respectively, where UNC_t denotes the date t uncertainty indicator. Again, we estimated the models using Maximum Likelihood and tested the residuals to confirm that at the standard level of significance there were no residual ARCH effects or serial correlation post estimation. The results for the three *GEU* cases, the two *EPU* cases and the BBD case are presented in columns (3)–(8) in Panel A in Table 6. The corresponding estimated standard deviations are plotted in Fig. 6.[31] The case using the basic economic-extended uncertainty-policy measure, *EPU2*, was found to be explosive and is therefore not reported.

Finally, we estimated a series of asymmetric E-GARCH models since, in financial data, negative shocks often produce greater subsequent volatility than positive shocks. The models were again estimated with and without the uncertainty indicators to explore what impact, if any, the addition of uncertainty had on the results. In each case, the mean equations were identical to the GARCH ones, while the variance equations took on one of the following two forms:

$$\log(h_t) = \omega + a|\varepsilon_{t-1}|/\sqrt{h_{t-1}} + b\log(h_{t-1}) + d\varepsilon_{t-1}/\sqrt{h_{t-1}} \quad \text{(without uncertainty)}$$

[30] This approach is similar to the one used by Hammoudeh and Yuan's (2008) to examine the effects of oil shocks on volatilities.

[31] There were a few cases where two local maximums were found. In these cases we report the one that maximized the likelihood function.

$$\log(h_t) = \omega + a|\varepsilon_{t-1}|/\sqrt{h_{t-1}} + b\log(h_{t-1}) + d\varepsilon_{t-1}/\sqrt{h_{t-1}} + \tau Unc_t \quad \text{(with uncertainty)}$$

For all cases except the one using the basic economic-extended uncertainty-policy, *EPU2*, we found the AR(1)-EGARCH(1,1) to be a valid specification. The estimated coefficients and robust standard errors for these cases are presented in Panel B of Table 6 and the estimated standard deviations are again depicted in Fig. 6.

The results in panel A of Table 6 highlight a number of interesting findings. First, we see that the coefficients on the uncertainty indicators in the mean equations all indicate stock returns drop as uncertainty rises. These effects are generally significant at conventional levels and reinforce the findings of Pastor and Veronesi (2012), Brogaard and Detzel (2012), Antonakakis, Chatziantoniou, and Filis (2013) and Alexopoulos and Cao (2012). Second, for all cases, the coefficients on the news-based uncertainty variables in the variance equations are positive and highly significant — suggesting that an increase in uncertainty pushes up volatility.[32] Furthermore, all coefficients on the lagged squared residuals (the ARCH effects) become statistically insignificant and the *b* coefficients (the GARCH effects) become negative — although in four of these 6 cases, the negative coefficients are not statistically significant. While these coefficients could result in negative estimates of the conditional variances, the estimates presented in Fig. 6, show this does not occur over our time period.

The plots in Fig. 6 associated with the GARCH(1,1) models illustrate that periods of heightened uncertainty (the stock market crash in 1987, the Asian and Russian Crises, 9/11 and the Gulf Wars) appear to be times of relatively high volatility. On the other hand, the plots also highlight significant differences across the various estimates of volatility. For example, the baseline estimates display much less volatility (as does the basic economic-basic policy uncertainty measure) in comparison with historical volatility based on daily S&P 500 returns, while the *GEU* cases using the basic economic language, display far more (likely due to the high negative value of b).[33] In contrast, the conditional volatility estimates based on extended economic-extended uncertainty (*GEU3* and *EPU3*), BBD, and basic economic-basic policy uncertainty (*EPU1*), are the most similar to the historical volatility estimates.

Panel B of Table 6 reports the estimates associated with the E-GARCH models. The first notable finding is that there is no strong evidence of an asymmetry. Second, while the ARCH effect is significant at the 5% level in the baseline case, once the uncertainty measures are added to the equations, there are only two cases where we find evidence of a remaining ARCH effect at a 10% level of significance. Third, out of the six cases with the uncertainty included, we again find that increased uncertainty decreases stock returns. Additionally, the results for the variance equations also reveal statistically significant coefficients on the uncertainty measures. In five of these cases, the coefficient on uncertainty is positive, again suggesting that an increase in uncertainty is linked to higher volatility. In these cases the GARCH effect is again negative, and in two, statistically insignificant.

The estimated standard deviations from the E-GARCH models, displayed in Fig. 6, show increased variance in times of heightened uncertainty — as we noted earlier. However, in some cases the volatility around 9/11 now exceeds that of the 1987 stock market crash. Significant differences across the estimated volatilities remain. Both the baseline and the extended economic-extended policy uncertainty (*EPU2*) cases are less volatile over time than historical volatility. In all other cases, the variability in volatility over time exceeds that of the baseline, with the *GEU3* case coming closest to the pattern of spikes seen in the historical and implied volatilities.

To summarize briefly, the results generally suggest that increases in *GEU* and *EPU* uncertainty cause stock returns to fall and volatility to rise, findings that hold for virtually all cases considered. Moreover, the inclusion of the news-based uncertainty measures reduces the impact of the ‘news’ contained in the ε's on estimated volatility.

5. Conclusions

In an effort to capture the effects of uncertainty shocks on the U.S. economy, we present newly designed indicators of aggregate and policy uncertainty based on a textual analysis of information contained in the New York Times — the long-standing newspaper of record in the US. We use the new measures, first, to identify the pattern of general uncertainty between 1985 and 2007, second, to isolate fluctuations in policy-related uncertainty, and, third, to identify the impact of these shocks on the economy, cycles, and the stock market.

Our VAR analysis, based on a series of six news-based indicators (three measure general economic uncertainty and three measure economic policy uncertainty) and BBD's blended economic policy uncertainty index, reveals that both types of uncertainty shocks cause significant recessions in the U.S. In particular, when a major shock like 9/11 hits, we estimate that output decreases 1%–4.5%, employment falls by 0.6%–2.2%, investment drops 3.5%–9.7%. These shocks are also a non-trivial source of short run fluctuations.

When comparing the results obtained using the different indices, we generally find that the basic economic-extended uncertainty indicator explains more of the variance in industrial production, employment, and investment than the other indicators do. We also note that the share of the variance attributable to BBD's blended *EPU* index is, in most cases, similar to that obtained using an economic policy index created using the basic economic and extended uncertainty language.

We also examined the impact of *GEU* and *EPU* shocks on stock returns and volatility by estimating a series of GARCH and E-GARCH models. Overall, we find evidence that an increase in uncertainty (as measured by our new indicators) significantly decrease returns on the S&P 500, and increases stock market volatility. Further, when the uncertainty indicators are included in the models, the ARCH effects typically become statistically insignificant.

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[32] Mensi, Hammoudeh, and Yoon's (2014) results also suggest that unpredicted news announcements can significantly affect volatility on the foreign exchange markets.

[33] Tsay (2010) also finds the estimated monthly volatility based on the daily S&P results to be higher than the volatility estimated using a GARCH(1,1) on monthly return data.

In addition to providing evidence that uncertainty shocks have powerful effects on the economy and the stock market, the paper also illustrates the usefulness of the textual analysis in developing measures of sentiments such as uncertainty. As we show in the paper, the use of language lists allows us to pinpoint articles that deal with uncertainty raising events and to link them to specific sources. Although we focus in this paper on general economic and policy uncertainty, it is possible with these word lists, to examine other groupings – taxation, government programs, immigration, election results, and terrorism – to provide further insights into important sources of uncertainty and determine their effects on the economy. This approach need not be restricted to a single newspaper, to the print media, or even to a single country. As such, the research potential of this approach is large and potentially very fruitful.

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Appendix A, B and C. Supplementary data and materials

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.iref.2015.02.002.

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