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A machine learning approach to identifying different types of uncertainty

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HIGHLIGHTS

- We construct a measure of uncertainty from Federal Reserve Beige Books (1970–2018).
- We distinguish uncertainty by type and find that not all uncertainty is the same.
- *Politics & Government Uncertainty* does not relate to changes in the economy.
- *Economic & Business Uncertainty* is associated with weakness in the economy.

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ABSTRACT

We implement natural language processing techniques to extract uncertainty measures from Federal Reserve Beige Books between 1970 and 2018. Business and economic related uncertainty is associated with future weakness in output, higher unemployment, and elevated term premia. On the other hand, political and government uncertainty, while high during recent times, has no statistically significant impact on the economy.

1. Introduction

Uncertainty plays a significant a role in shaping investment decisions, household spending patterns, and labor market outcomes, with the potential for large cross-border spillover effects (e.g., Klößner and Sekkel 2014). Unfortunately, very few concepts are simultaneously as important and as difficult to measure, leading to significant efforts to quantify uncertainty through survey-based measures of disagreement among professional forecasters (e.g., Bachmann et al. 2013); option-implied measures of volatility around future asset prices (e.g., VIX); and news-based measures of reported uncertainty (e.g., Baker et al. 2016).

2. Measuring uncertainty

We develop a natural language processing model (combining a trained support vector machine classifier, deterministic algorithms, and manually created graph pattern rules) using *Amenity Analytics*'s text mining engine to extract uncertainty measures from Federal Reserve Beige Books, published between 1970 and 2018.[1]

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[1] Our method builds from other papers that have taken advantage of machine learning (e.g., Azqueta-Gavaldón 2017) by using natural language processing techniques with deep learning beyond topic modeling, similar to the algorithm in Boudoukh et al. (2016). There is also a growing literature capitalizing on computational linguistics algorithms to analyze FOMC transcripts and other forms of central bank communication (e.g., Hansen et al. 2017).

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The outlook among contacts was cautiously optimistic, with significant uncertainty related to domestic politics.

Fig. 1. Example of Identified Uncertainty from January 18, 2017 Beige Book, p. A-2.

Our proposed measure counts every time the concept of "uncertainty" is mentioned in the text. Importantly, our model recognizes negation links that separate instances of uncertainty reduction from negative mentions of uncertainty in the economy. For example, the sentence "there is uncertainty in the economy" would increase the count by one. If it instead read, "there is *not* uncertainty in the economy", it would reduce the count by one. This capability is unique in the literature, as common algorithms treat words as features, and search for set combinations in text without being able to account for context. Moreover, the multi-functional extraction capabilities of the engine, also allow us to extract slotted terms in addition to sentiment, such that we not only identify the word "uncertainty" in a sentence, but we are also able to contextually classify the *type* of uncertainty being extracted. Fig. 1 shows a sentence with slots around the two areas identified: "domestic" and "politics" that relate to "uncertainty".

We define the uncertainty count for each Beige Book $i = 1, 2, \ldots, I$, as the difference between the negative and positive uncertainty mentions divided by the word count for each Beige Book, to control for the tendency of documents to become lengthier over time:

$$\upsilon_i = \left[\frac{\begin{array}{c}(\text{number of negative uncertainty extractions in Beige Book } i)\\ -(\text{number of positive uncertainty extractions in Beige Book } i)\end{array}}{(\text{word count in Beige Book } i)} \right] \times 10,000. \tag{1}$$

The aggregate quarterly measure of uncertainty is the sum of the scaled count of each Beige Book in a given quarter, t,

$$U_t = 100 + \sum_{i \in \text{quarter } t} \upsilon_i. \tag{2}$$

3. Quantifying different types of uncertainty

Beyond the main index of uncertainty, we use Eqs. (1) and (2) to distinguish among 13 different areas of uncertainty. We apply principal component analysis and find that the areas can be classified into two broader categories (see Fig. 2).

The areas in groups 1 and 4 both contribute heavily to the second principal component ($>|0.5|$). We combine these groups (e.g., "fiscal", "regulation", etc.) into *Politics & Government (P&G) Uncertainty*. In contrast, groups 2 and 3 are mostly explained by the first component and combined into *Business & Economics (B&E) Uncertainty*. Importantly, given the low factor contribution of the components (0.22 and 0.13), we identify these two categories to be quite different, suggesting that uncertainty differs by type and a simple word count would miss this important distinction.[2]

Fig. 3 depicts the overall index of *Uncertainty* and its two categories over time. Our uncertainty measure is broadly similar to the economic policy uncertainty measure of Baker et al. (2016) during the 1985–2018 period (0.68 correlation). Moreover, *P&G Uncertainty* correlates highly (0.55–0.66) with similar measures, such as tax expiration and categorical uncertainty on taxes, fiscal policy, government spending, health care, and entitlement programs.

4. Assessing the impact of different types of uncertainty on the economy

In order to explore the relationship between uncertainty and the real economy, we specify a quarterly vector auto-regressive (VAR) framework, similar to Baker et al. (2016), from 1970-Q2 to 2017-Q4.[3] We let uncertainty be followed by the unemployment rate and (log) GDP, as well as the federal funds rate and the (log) S&P 500 Index, in order to control for business-cycle and general financial conditions.

The first column in Fig. 4 shows the response to a shock to *Uncertainty*, while the second and third columns, show the responses to a shock to *B&E* and *P&G Uncertainty*, respectively. A one standard deviation increase in *Uncertainty* is about 2.8 points. To provide some context, this magnitude is roughly equal to the increase from the average level of uncertainty in 2005–2006 to 2007–2008. Notoriously, the uncertainty index has muted effects; but when divided into categories, it is clear that *B&E Uncertainty* is associated with economically and statistically significant changes in the economy; whereas *P&G Uncertainty* is not.

A one standard deviation shock to *B&E Uncertainty* relates to an increase in the unemployment rate of 0.3%.[4] This effect is statistically significant at the 90 percent confidence level and quite persistent, lasting for over 3 years. A shock to *B&E Uncertainty* is also associated with a decline in economic activity of about 1.8%.[5]

The impact of *B&E Uncertainty* shocks is in line with the effects of other publicly available measures of uncertainty, such as the financial and macroeconomic uncertainty indices from Jurado et al. (2015); the historical economic policy uncertainty index from Baker et al. (2016); and the financial uncertainty index from Chuliá et al. (2017).

The main results are robust to altering the order of the variables so that uncertainty is first, in the middle, or last; allowing for different lags as specified by several information criteria rules; including different variables to control for general optimism/pessimism in financial markets; incorporating the shadow rate to account for the stance of monetary policy during the zero lower bound period; first-differencing variables; excluding the unemployment rate; considering non-farm payroll employment; and removing the zero lower bound period.

In all cases, the same results hold: *B&E Uncertainty* is associated with stronger, more persistent, and statistically significant changes in the real economy, whereas *P&G Uncertainty* is not.[6]

2 This result is consistent with work by Larsen (2017), who finds that various types of uncertainty from news paper articles in Norway have different effects on the economy.

3 It is worth noting that a structural model is necessary to identify the causal effects of uncertainty and deal with potential endogeneity as in Richter and Throckmorton (2017).

4 This magnitude is consistent with the response of the unemployment rate to different uncertainty shocks previously found in the literature: 0.05 p.p. (Bundick et al., 2017); 0.08% (Creal and Wu, 2017); 0.15% (Castelnuovo and Tran, 2017); 0.2 p.p. (Leduc and Liu, 2012); 0.25%-0.4% (Mumtaz, 2018).

5 In their quarterly VAR specification, Baker et al. (2016) found uncertainty to lower GDP by 1.2%. Others have identified a decline in industrial production with similar magnitudes: 0.25% (Husted et al.); 0.4% (Bundick et al., 2017); 1% (Choi, 2013); 1.2% (Baker et al., 2016); 1% during expansions and 2% during recessions (Caggiano et al., 2017).

6 A potential explanation is that *P&G Uncertainty* captured in the Beige Books is not associated with changes in the real economy because it reflects uncertainty that is perhaps already priced in the economy or agents do not believe these documents provide special insight into fiscal policy.

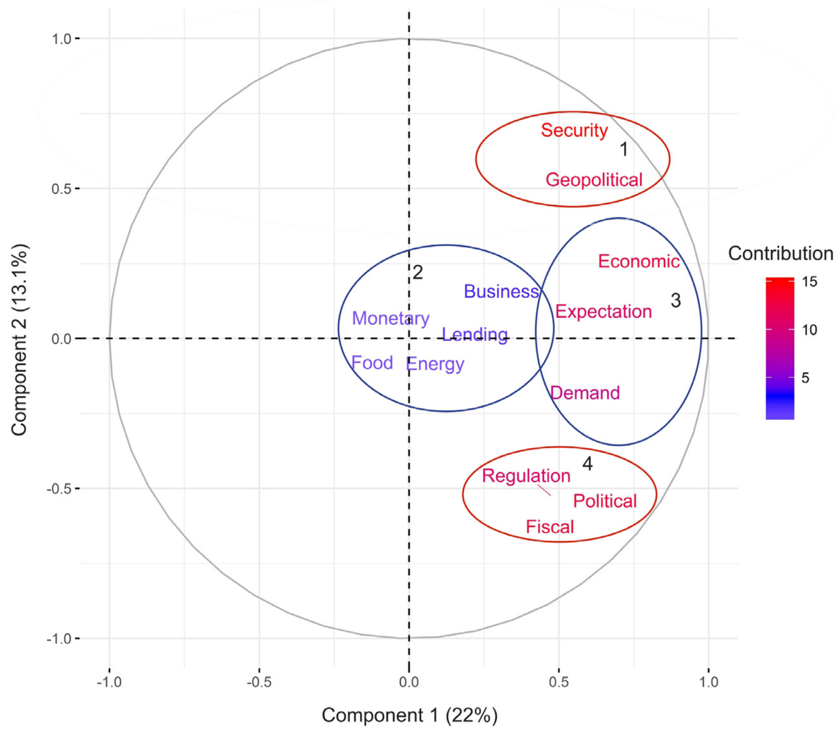

Fig. 2. Contribution of components. *Notes*: Components 1 and 2 are extracted by principal component analysis on all 13 measures of uncertainty extracted from the Beige Books.

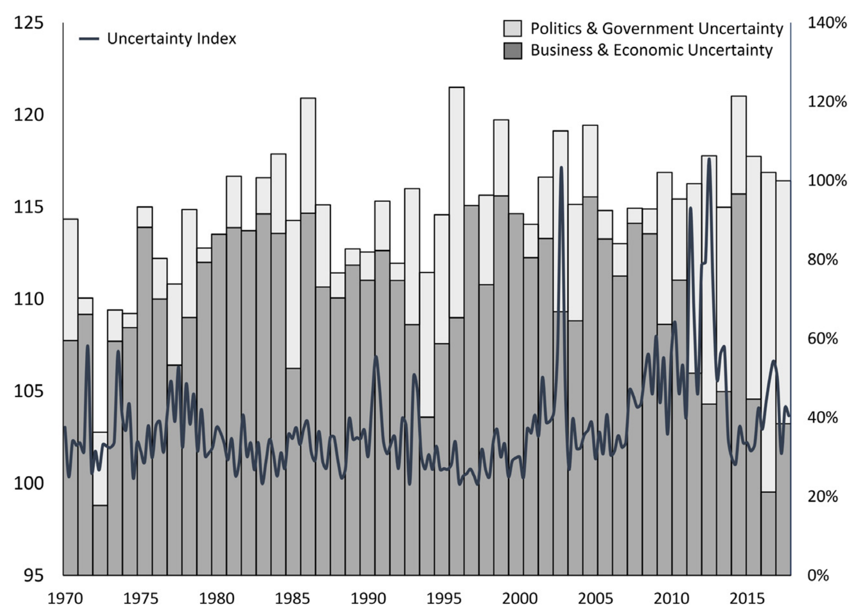

Fig. 3. Uncertainty index and categories over time. *Notes*: The stacked bars show the proportion of each category relative to the overall index, which might not necessarily add up to 100% since one mention of uncertainty could be counted towards both categories at the same time. Similarly, if uncertainty is not classified into any category, the total will be less than 100%.

Bundick et al. (2017) propose a slightly different specification to study the response to uncertainty shocks in a VAR framework by ordering their policy uncertainty measure after production (GDP) and prices (PPI), consistent with the notion that the economy responds to shocks with a lag. After the uncertainty index, we also incorporate the federal funds rate and the slope of the yield curve, defined as the 10-year yield minus the 3-month yield, similar to their main specification. The results from this identification also suggest that a standard deviation increase in *B&E Uncertainty* is associated with a 1% decline in future GDP, while there is no statistically significant relationship between higher *P&G Uncertainty* and GDP.[7]

Importantly, we find that higher *B&E Uncertainty* is associated with future steepening of the yield curve — an increase in the

[7] We find that higher uncertainty is associated with higher PPI, although not statistically significant at the 90% confidence level. This result is consistent with Creal and Wu (2017), who also found higher uncertainty relates to higher (but not statistically significant) inflation. Others have found that uncertainty leads to lower CPI inflation around 0.15%–0.8% (Husted et al.; Leduc and Liu, 2012; Castelnuovo and Tran, 2017; Caggiano et al., 2017).

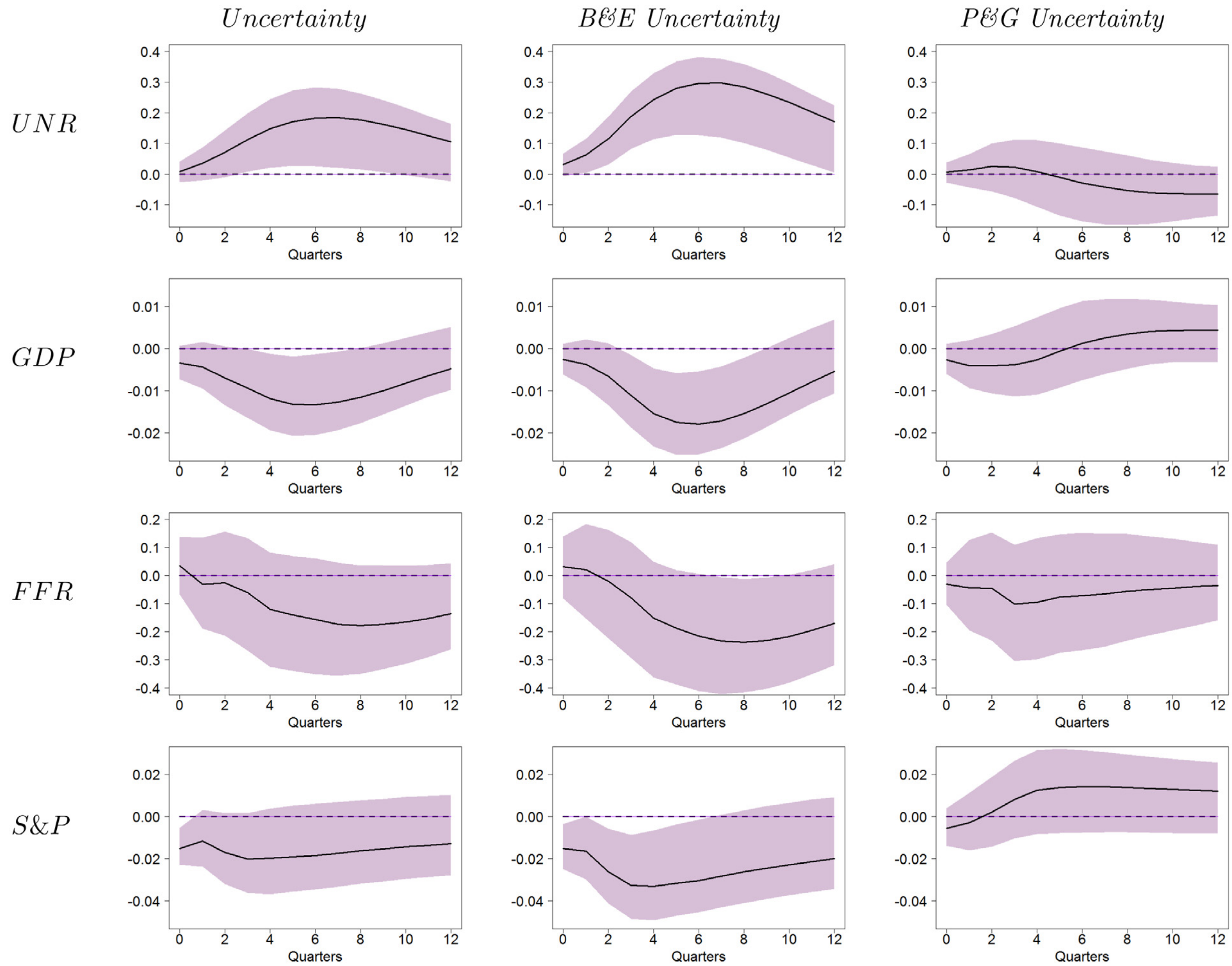

Fig. 4. Impulse Responses to *Uncertainty*, *B&E Uncertainty*, and *P&G Uncertainty* Shocks. *Notes*: The first column shows the response of a shock to *Uncertainty* to the unemployment rate, GDP, the Federal Funds Rate, and S&P 500. The second and third columns show the same impulses for a shock to *B&E* and *P&G Uncertainty*, respectively. Impulse responses are estimated via Cholesky decomposition with the corresponding 90% confidence intervals with 10,000 Bootstrap iterations from a VAR of order 3. For data sources, details on the main specification, and robustness checks, refer to the Online Appendix.

slope of 10 basis points. In order to further explore the channels through which *B&E Uncertainty* operates, we run different VAR specifications and find that this increase in the slope is due to an increase in the 10-year yield and not necessarily a decline in the short end of the yield curve. Our findings indicate that *B&E Uncertainty* is more likely related to long-term expectations of economic activity; in particular, we find a statistically significant relationship with the 10-year term premium. These results suggest that the *B&E Uncertainty* that is documented on Federal Reserve Beige Books captures future perceived weakness in the economy, for which investors' demand a higher premium to invest in long-term bonds. This premium is above and beyond the expected future path of the short rate, captured by the risk-neutral yield, suggesting that *B&E Uncertainty* is not necessarily related to forward guidance and the clarity provided by the Fed about the future path of interest rates, but is instead related to the risk component embedded in the term premium.[8] Finally, we explore the relationship of *B&E Uncertainty* and the U.S. dollar and find that a one standard deviation increase in *B&E Uncertainty* is associated with a 1% future depreciation of the currency, consistent with expected economic weakness.

[8] Consistent with the notion that *B&E Uncertainty* captures uncertainty about future economic activity, we find that higher *B&E Uncertainty* is associated with higher credit spreads — the risk priced by the difference between Moody's Seasoned Baa corporate bond rate and the federal funds rate.

5. Conclusion

Although uncertainty in the U.S. has remained elevated in these past few years, our methodology reveals that this is more likely related to politics and government and not the overall health of the economy, with negligible effects on economic activity. This finding is consistent with the recent decoupling of certain measures of uncertainty and general financial conditions observed in the U.S. We propose that along with quantifying uncertainty, it is important to also distinguish the type of uncertainty that is being measured.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2018.07.003.

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