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Economic policy uncertainty, financial markets and probability of US recessions

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HIGHLIGHTS

- Economic policy uncertainty indexes (IEPU) help predict future US recessions.
- IEPUs improve forecasts from probit models with financial variables.
- The results hold for in-sample and out-of-sample forecasts at longer horizons.
- The newspaper-based index is a robust predictor at the longer forecast horizons.

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ABSTRACT

We use probit recession forecasting models to assess the ability of economic policy uncertainty indexes developed by Baker et al. (2013) to predict future US recessions. The model specifications include policy indexes on their own, and in combination with financial variables, such as interest rate spreads, stock returns and stock market volatility. Both in-sample and out-of-sample analysis suggests that the policy uncertainty indexes are statistically and economically significant in forecasting recessions at the horizons beyond five quarters. The index based on newspaper reports emerges as the best predictor, outperforming the term spread at the longer forecast horizons.

1. Introduction

Indexes of economic policy uncertainty (IEPU) constructed by Baker et al. (2013) have received increasing attention among researchers and policy-makers. We evaluate the possible use of these indexes in forecasting. In particular, we ask: "*Can the IEPUs predict future US recessions? If so, do they contain information that has not already been incorporated by the financial markets?*" These questions are novel, as previous studies have focused on the relation between the IEPUs and continuous measures of economic activity (e.g. Baker et al., 2013; Colombo, 2013).

Macroeconomic theory provides guidance as to why the IEPUs can forewarn recessions. Increased uncertainty about fiscal policy, for example, can cause a delay in investment and hiring decisions, which in turn can trigger a prolonged downturn. The downturn is likely to be followed by an economic rebound after the policy uncertainty is resolved (Fernández-Villaverde et al., 2011; Born and Pfeifer, 2013).[1]

We evaluate the in-sample and out-of-sample forecasting performance of the IEPUs using probit recession forecasting models, as defined in Estrella and Mishkin (1998). The IEPUs are statistically and quantitatively important in forecasting US recessions at the forecast horizons beyond five quarters. Furthermore, including

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[1] Bloom (2014) reviews macroeconomic effects of time-varying uncertainty.

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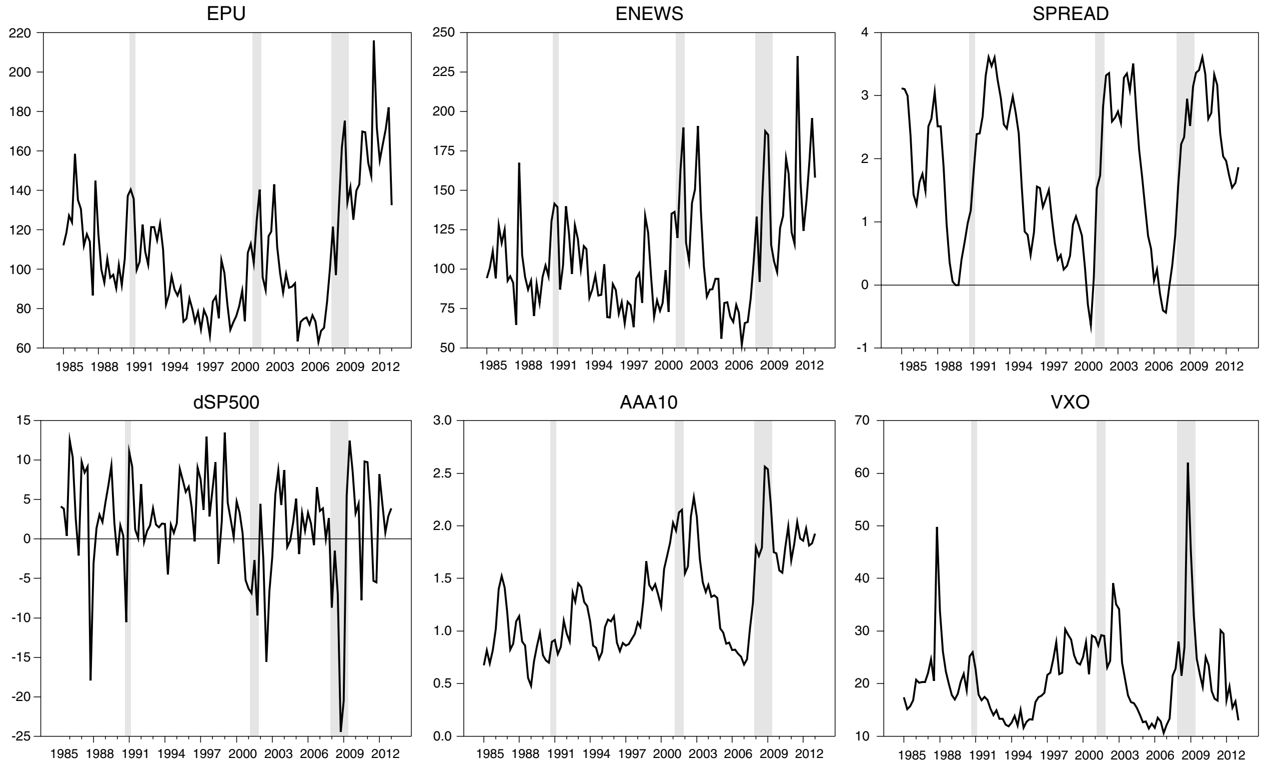


Fig. 1. Time series with the shaded NBER recession dates.

the IEPUs into the models with financial variables improves the accuracy of the forecasts.

2. Method and data

Our empirical framework is based on probit recession forecasting models. Such models have been previously used to test the forecasting properties of financial variables.[2] Despite their simplicity, probit models with the term spread generate recession forecasts that are often comparable and in some cases superior to those of more sophisticated models, as well as to the responses of professional forecasters. This framework provides a consistent and parsimonious way of comparing the predictive content of individual variables at different forecast horizons. Similar to Estrella and Mishkin (1998), we use two evaluation criteria: the significance of the regression coefficients and the measures of fit.

We first estimate one-factor models, which include an IEPU or a financial indicator x_t:

$$P\left(R_{t+k}=1\right)=F\left(\alpha+\beta x_t\right), \tag{1}$$

where R_{t+k} is the zero–one recession indicator in period $t+k$, with k denoting the forecast horizon. Following a common convention, we define a recession as a period between the peak and the subsequent trough plus the trough itself, using the business cycle dates from the National Bureau of Economic Research (NBER). Finally, F denotes the cumulative normal distribution. If the β coefficient is statistically significant, then x is useful for forecasting a recession k periods ahead. The quantitative importance of each variable is measured by pseudo R^2, developed by Estrella (1998).

We use two IEPUs: an aggregate index (EPU) and its newspaper-based component (ENEWS). The choice of financial variables is based on the extensive analysis of Estrella and Mishkin (1998) and Fornari and Lemke (2010). The term spread (SPREAD) is the difference between the 10-year and 3-month US Treasury yields. The stock returns (ΔSP500) is the log-difference of the S&P 500 index. The corporate spread (AAA10) is the Aaa corporate bond yield relative to the yield on 10-year Treasury. In addition, we include stock market volatility as a common proxy for economic uncertainty. It is measured by the VXO index, combined with the realized volatility from Bloom (2009) for 1985. Fig. 1 plots our series for the whole sample 1985:Q1–2013:Q1.[3]

To answer our second research question, we estimate multi-factor models

$$P\left(R_{t+k}=1\right)=F\left(\alpha+\beta x_t+\gamma \mathrm{SPREAD}_t+\delta' Z_t\right), \tag{2}$$

where x_t is an IEPU or a financial variable, and Z_t is a vector of controls.[4] The models always include SPREAD, due to its well-known forecasting properties. If β for an IEPU remains significant in (2), then this index provides information above and beyond of what is captured by the financial markets. Pseudo R^2s measure the quantitative importance of the IEPUs.

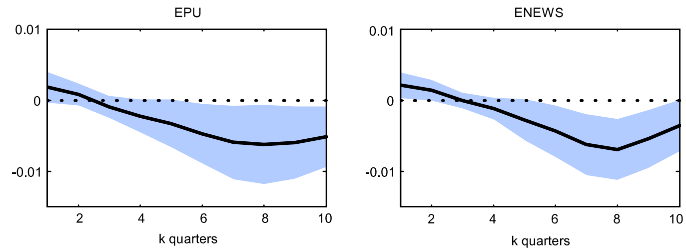
3. Results

Probit models are estimated by maximum likelihood. In-sample results are for the whole period. Out-of-sample results are based on the recursive estimation, which keeps the same prediction sample 2006:Q1–2013:Q1 for all forecast horizons. Note that the 2007–2009 recession is included into out-of-sample forecasting. In all cases, we consider the forecast horizons from one to ten quarters.

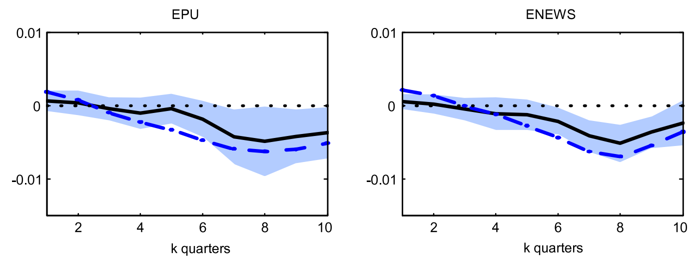
[2] See Wheelock and Wohar (2009) for a recent survey, and online Appendix for references.

[3] The IEPUs are from http://www.policyuncertainty.com. The financial variables are from the FRED database (http://research.stlouisfed.org/fred2/), and www.cboe.com/VXO.

[4] Z_t can include up to two financial variables, but can also represent the null set.



A. $P(R_{t+k} = 1) = F(\alpha + \beta x_t)$.



B. $P(R_{t+k} = 1) = F(\alpha + \beta x_t + \gamma \text{SPREAD}_t + \delta \Delta\text{SP500}_t)$.

Fig. 2. Average marginal effects of the policy uncertainty indexes. Notes: The solid lines are the average marginal effects of x_t on a recession probability k quarters ahead, based on a separate model for each horizon. The title of each panel indicates x. Shaded are the areas between ± one standard deviation of the marginal effects. The dashed–dotted lines reproduce the estimates from the one-factor models.

Table 1
In-sample pseudo R^2s for $P(R_{t+k} = 1) = F(\alpha + \beta x_t)$; 1985:Q1–2013:Q1.

x_t/k	1	2	3	4	5	6	7	8	9	10
EPU	0.045	0.007	0.007	0.036	0.073	0.125	0.175	0.194	**0.179**	**0.140**
NEWS	0.091	0.028	0.000	0.013	0.063	0.123	0.210	**0.254**	0.170	0.091
SPREAD	0.002	0.033	**0.110**	**0.189**	**0.256**	**0.281**	**0.252**	0.219	0.165	0.113
ΔSP500	**0.214**	**0.110**	0.039	0.011	0.001	0.010	0.004	0.003	0.012	0.011
AAA10	0.100	0.041	0.008	0.000	0.007	0.043	0.082	0.090	0.060	0.031
VXO	0.140	0.072	0.006	0.001	0.003	0.015	0.034	0.048	0.031	0.015

Notes: The best forecast for each horizon is in bold.

3.1. Marginal effects

Fig. 2 plots the average marginal effects of the IEPUs on the recession probabilities, along with the confidence bands, computed with the robust standard errors from Estrella and Rodrigues (1998). This figure illustrates the significance of the IEPUs.

In the one-factor models, the marginal effects of both IEPUs peak at eight quarters, and are statistically significant for several horizons. Since the IEPUs take only positive values by construction, the signs of the marginal effects coincide with the signs of β in (1) and (2). Thus an increase in an IEPU signals a higher recession probability in the short-run, but a lower probability in the long-run. Fernández-Villaverde et al. (2011) and Born and Pfeifer (2013) predict that an adverse shock to fiscal policy uncertainty triggers a contraction in output (with the peak response several quarters after the shock), which is followed by an economic rebound. Bloom (2009) emphasizes similar "bust-boom" dynamics of shocks to economic uncertainty. The sign reversal of the marginal effects of the IEPUs is consistent with these theoretical predictions. However, the sign reversal cannot be taken as direct evidence of the causal effects of policy uncertainty on the economy, since we do not identify structural uncertainty shocks.

Panel B of Fig. 2 demonstrates that the statistical significance of ENEWS at the longer horizons is little affected by the term spread and stock returns. This result also holds in the models with other combinations of financial variables. The significance of EPU is less robust. This index remains consistently significant in multi-factor models only for the ten quarters ahead.

3.2. Measures of fit

The IEPUs are not only statistically significant, but also quantitatively important for recession forecasting. This conclusion is based on the relative ranking of measures of fit in Tables 1 and 2. For one-factor models, we report both in-sample and out-of-sample pseudo R^2s. For multi-factor models, we focus on the out-of-sample performance.[5] Accuracy in predictions for periods beyond the estimation sample is a stricter evaluation criterion, since additional variables do not always increase out-of-sample fit.

Our main finding is the strong predictive content of ENEWS at the horizons beyond five quarters. ENEWS outperforms the term spread on its own when $k = 8$ and $k = 9$, both in- and out-of-sample. The highest measures of fit for horizons from six to nine quarters involve ENEWS. For example, adding ENEWS to SPREAD and ΔSP500 increases the out-of-sample pseudo R^2 by 0.25 when $k = 8$. We also find that the EPU index improves the forecast accuracy at the ten-quarter horizon. In comparison, the best forecasting model with financial variables alone, at the longer forecast horizons, includes the term and the corporate spreads.[6] Table 2 indicates that probit models with ENEWS outperform this specification.

Fig. 3 plots the predicted recession probabilities from four probit models, and illustrates the usefulness of ENEWS. The results

5 In-sample pseudo R^2s in online Appendix provide a similar relative ranking.

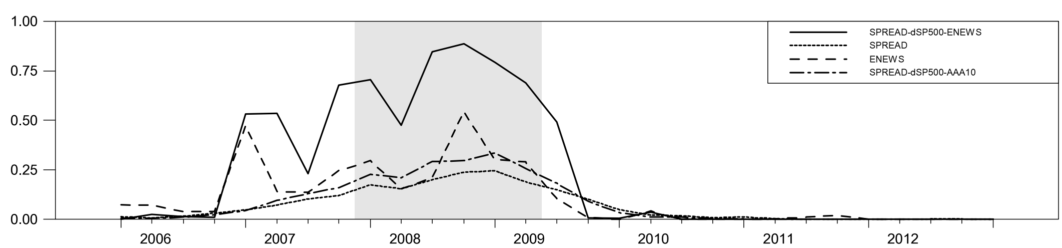
6 Neither AAA10 nor VXO is statistically significant in the models with SPREAD and ΔSP500 for any horizon.

Table 2
Out-of-sample pseudo R^2s; 2006:Q1–2013:Q1.

x_t/k	1	2	3	4	5	6	7	8	9	10
A. $P(R_{t+k}=1)=F(\alpha+\beta x_t)$										
EPU	−0.100	−0.094	−0.027	**0.070**	0.131	0.306	0.412	0.459	0.441	0.358
ENEWS	0.005	−0.034	−0.042	0.022	0.059	0.296	0.461	0.554	0.419	0.218
SPREAD	−0.088	−0.263	−0.966	−1.432	0.312	0.602	0.583	0.524	0.407	0.278
ΔSP500	**0.450**	**0.222**	−0.007	−0.005	−0.051	−0.024	−0.006	0.002	−0.033	−0.022
AAA10	0.244	0.059	−0.073	−0.099	−0.030	0.098	0.207	0.211	0.106	−0.043
VXO	0.348	0.175	−0.044	−0.082	−0.050	−0.043	0.001	−0.043	−0.209	−0.478
B. $P(R_{t+k}=1)=F(\alpha+\beta x_t+\gamma \text{SPREAD}_t)$										
EPU	−0.266	−0.413	−1.115	−1.817	0.069	0.661	0.700	0.669	0.559	**0.422**
ENEWS	−0.148	−0.283	−0.895	−1.681	−0.152	**0.679**	0.761	0.762	**0.597**	0.379
ΔSP500	0.413	0.090	−0.686	−1.025	−0.143	0.600	0.587	0.533	0.379	0.244
AAA10	0.322	0.041	−0.964	−2.070	0.312	0.604	0.625	0.524	0.231	−0.176
VXO	0.261	0.008	−0.657	−1.244	**0.337**	0.633	0.665	0.620	0.457	0.237
C. $P(R_{t+k}=1)=F(\alpha+\beta x_t+\gamma \text{SPREAD}_t+\delta\Delta\text{SP500}_t)$										
EPU	0.169	−0.091	−0.761	na	−0.280	0.639	0.709	0.706	0.528	0.378
ENEWS	0.266	0.009	−0.962	−2.075	−0.547	0.667	**0.776**	**0.788**	0.574	0.303
D. $P(R_{t+k}=1)=F(\alpha+\beta x_t+\gamma \text{SPREAD}_t+\delta \text{AAA10}_t)$										
EPU	−0.121	−0.287	−0.802	−1.557	0.086	0.674	0.761	0.755	0.583	0.322
ENEWS	−0.035	−0.219	−0.814	−1.530	−0.554	0.671	0.764	0.773	0.566	0.279

Notes: Statistics are based on the recursive estimation. In the case of 'na', the pseudo R^2 could not be calculated due to the problem of overfit. The best forecast for each horizon is in bold. Negative values indicate a poor fit.

A. Six-quarter-ahead forecasts.



B. Eight-quarter-ahead forecasts.

Fig. 3. Out-of-sample predicted recession probabilities with the shaded NBER recession dates.

are based on the recursive estimation, which takes into account the availability of financial data and an average 12 month delay of the NBER announcements. For example, the first forecast for 2006:Q1 on Panel A is constructed with the data from 2004:Q3 and the probit model with $k = 6$, estimated over the sample 1985:Q1–2003:Q3. Other forecasts are obtained by reestimating the models each subsequent quarter. Fig. 3 indicates that the model with ENEWS, SPREAD and ΔSP500 would have been sending stronger warning signals about the 2007 recession, relative to other specifications.

3.3. Robustness

Our main finding of the forecasting dominance of ENEWS at the longer horizons is robust to: (i) including the business cycle peak into a recession period; (ii) a comparison with the EPU sub-components constructed from forecast dispersions about government spending and inflation; (iii) the use of the mean absolute error as a measure of fit; and (iv) the logistic distribution for the F function.

Online Appendix includes additional robustness checks. First, we establish that ENEWS enhances the predictive content of the financial variables at the longer horizons even in the presence of the lagged independent variables. Second, we explore forecasting properties of a historical (still experimental) index of economic policy uncertainty BETA,[7] which goes back to 1900. We find that BETA is statistically significant in the probit models for many forecast horizons on its own, and in combination with stock returns. Its quantitative importance in predicting US recessions, as measured by in-sample pseudo R^2, is relatively small, albeit often exceeding that of the stock returns. Finally, we show that the monthly ENEWS index is useful in forecasting recessions at the horizons from 18 to 25 months.

[7] http://www.policyuncertainty.com.

4. Conclusions

The ENEWS index, which is constructed from newspaper reports related to economic policy uncertainty, emerges as a robust predictor in forecasting future US recessions at the longer forecast horizons (six to nine quarters ahead in the quarterly sample). At these forecast horizons, ENEWS enhances the forecasting performance of the financial variables. The possible use of the IEPUs in forecasting provides a rationale for publishing these indexes on a continuous basis. An interesting direction for future research is to examine forecasting properties the IEPUs of other countries.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.econlet.2014.09.018.

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