Christian Pierdzioch[1] / Rangan Gupta[2]

Uncertainty and Forecasts of U.S. Recessions

[1] Helmut-Schmidt-Universitat Universitat der Bundeswehr Hamburg, Hamburg, Germany, E-mail: c.pierdzioch@hsu-hh.de
[2] Department of Economics, University of Pretoria, Pretoria, South Africa, E-mail: rangan.gupta@up.ac.za

Abstract:
We estimate Boosted Regression Trees (BRT) on a sample of monthly data that extends back to 1889 to recover the predictive value of disaggregated news-based uncertainty indexes for U.S recessions. We control for widely-studied standard predictors and use out-of-sample metrics to assess forecast performance. We find that war-related uncertainty is among the top five predictors of recessions at three different forecast horizons (3, 6, and 12 months). The predictive value of war-related uncertainty has fallen in the second half of the 20th century. Uncertainty regarding the state of securities markets has gained in relative importance. The probability of a recession is a nonlinear function of war-related and securities-markets uncertainty. Receiver-operating-characteristic curves show that uncertainty improves out-of-sample forecast performance at the longer forecast horizons. A dynamic version of the BRT approach sheds light on the importance of various lags of government-related uncertainty for recession forecasting at the long forecast horizon.

Keywords: boosted regression trees, forecasting, recessions, ROC curves, uncertainty

JEL classification: C53, E32, E37

DOI: 10.1515/snde-2018-0083

1 Introduction

In the wake of the "Great Recession" there has been a renewed interest in the link between uncertainty and the macroeconomy, both in terms of theoretical and empirical research. Following on early works based on partial equilibrium models (Bernanke, 1983; Dixit and Pindyck, 1994), several researchers have developed in recent years dynamic stochastic general equilibrium models to capture the (negative) impact of uncertainty on macroeconomic variables (Bloom, 2009; Fernández-Villaverde et al. 2011; 2015; Gourio, 2012; Mumtaz and Zanetti, 2013; Bloom et al., 2014; Christiano, Motto and Rostagno, 2014; Carriero et al., 2015) At the same time, much significant empirical research has been undertaken to empirically validate the predictions of these theoretical models. For recent contributions to the rapidly growing strand of research on uncertainty and macroeconomic fluctuations, see Bachmann and Bayer (2013), Bachmann, Elstner, and Sims (2013), Born and Pfeifer (2014), Karnizova and Li (2014), Carriero et al. (2015), Jones and Enders (2016), Mumtaz and Theodoridis (2017), Creal and Wu (2017), Gupta and Jooste (2018), and Segnon et al. (2018), to name just a few.[1]

Understandably, in order to quantify the impact of uncertainty on the macroeconomy, one requires a measure of uncertainty, which is a latent variable that cannot be directly observed. In this regard, besides implied-volatility indices associated with financial market uncertainty (popularly called the VIX), three broad approaches have been proposed in the literature: (1) The news-based approach proposed by Brogaard and Detzel (2015) and Azzimonti (2018), Baker, Bloom, and Davis (2016), Caldara and Iacoviello (2016), Larsen (2017), and Manela and Moreira (2017). The main idea underlying this approach is to perform searches of newspapers for terms related to economic and policy uncertainty (EPU) and to use the results of this search to construct measures of uncertainty. (2) Carriero et al. (2015), Chuliá, Guillén, and Uribe (2017), Creal and Wu (2017), Jurado, Ludvigson, and Ng (2015), Ludvigson, Ma, and Ng (2015), Mumtaz and Zanetti (2013), Mumtaz and Theodoridis (2017), Mumtaz and Surico (2018), Mumtaz and Theodoridis (2018), and Shin and Zhong (2016) recover measures of uncertainty from estimates of various types of small and large-scale structural models related to macroeconomics and finance. (3) Bali, Brown, and Tang (2015), Rossi and Sekhposyan (2015), Rossi, Sekhposyan, and Soupre (2016), and Scotti (2016) propose to construct measures of uncertainty based on forecaster disagreement.

At this stage, it is important to highlight two observations that can be made about this recent literature on uncertainty: (1) While researchers have used all the above-mentioned three alternative approaches to measure uncertainty in empirical research, news-based measures perhaps are the most popular uncertainty measures. There are several reasons for this popularity: easy availability of data in the public domain for multiple countries and long sample periods; no estimation is required in order to obtain these measures; news-based measures

Christian Pierdzioch is the corresponding author.

of uncertainty can easily be categorized into various types of uncertainy associated with the general economy, government policies, financial markets, geopolitical risks, etc. (2) With a few exceptions (Karnizova and Li, 2014; Balcilar, Gupta and Segnon, 2016; Balcilar, Gupta and Jooste, 2017b; Junttila and Vataja, 2017; Segnon et al., 2018), empirical studies trying to recover the link between uncertainty and economic activity (as measured, for example, in terms of output and/or unemployment, investment, etc.) have been in-sample analyses.

Against this backdrop of limited evidence on the out-of-sample forecast performance of uncertainty measures with respect to subsequent developments of economic activity, and given the widely held view that the importance of variables and models should be judged based on out-of-sample validations, we report results that shed light on the contribution of disaggregated news-based measures of uncertainty to out-of-sample forecasting of U.S. recessions, as measured in terms of the National Bureau of Economic Research (NBER) recession indicator. Our historical sample period runs from January 1899 to February 2017. We report results for three forecast horizons (3, 6, and 12 months). Unlike earlier researchers, who focus on the forecasting properties of an aggregate news-based measure of uncertainty (Baker, Bloom and Davis, 2016), we use disaggregated measures of uncertainties as developed by Manela and Moreira (2017). They construct monthly text-based measures of uncertainties using front-page articles of the Wall Street Journal (in analogy to the VIX, they call their measure News Implied Volatility, NVIX), with disaggregated measures capturing uncertainty associated with government policy, financial intermediation, natural disasters, securities markets, wars, and those that cannot be classified.[2] Our research highlights the importance of categorizing uncertainty into its various components when it comes to forecasting U.S. recessions and, in the process, we emphasize the need to go beyond aggregate measures of uncertainty that have been studied in earlier research. Further, unlike the post World War II data-based works of Karnizova and Li (2014),[3] Balcilar, Gupta, and Segnon (2016), Balcilar, Gupta, and Jooste (2017b), Junttila and Vataja (2017), and Segnon et al. (2018), who study either only a measure of uncertainty and/or just a few predictors (like, for example, the term-spread), we not only consider a long historical sample period but we also control for multiple other predictors (the oil price, the inflation rate, the term-spread, the short-term interest rate, stock-market-related variables, and fluctuations of the real exchange rate) that have been widely studied in the recession-forecasting literature.

In order to inspect how the probability of U.S. recessions is linked to the various NVIX components, and whether these components help to forecast recessions, we use a Boosted Regression Trees (BRT) approach. The BRT approach brings together, in a unified framework, statistical boosting and regression trees. Boosting is a machine-learning technique that shows how to approximate a potentially complicated function known as a strong learner by means of an additive ensemble of so called base learners (on boosting, Freund and Schapire, 1997; Friedman, Hastie and Tibshirani, 2000; Friedman 2001; 2002; among others). In the case of our research, the weak learners are simple regression trees (on regression trees, see Breiman et al. 1984; for an excellent textbook exposition, see Hastie, Tibshirani and Friedman, 2009). The strong learner then combines the forecasts implied by a potentially large ensemble of regression trees and, hence, allows highly complicated links between the recession probability and predictors to be estimated. An advantage of regression trees is that they are robust to outliers in the data, and that they are insensitive to the inclusion of irrelevant data in the list of predictors. Special BRT techniques are available that can be used to gauge the relative importance of predictors and to describe their marginal effects on the recession probability.

Our results can be summarized as follows. We find that, according to a measure of the relative importance of predictors, the NVIX component that summarizes war-related uncertainty is among the top five predictors of recessions at three different forecast horizons (3, 6, and 12 months). In the second half of the sample period (the entire sample period, 1889–2017, covers more than a century of data), the NVIX component that captures uncertainty regarding the state of securities markets has gained in relative importance. Marginal-effects curves show that the probability of a recession is nonlinearly linked to war and securities-markets uncertainty.[4] An analysis based on receiver-operating-characteristic (ROC) curves shows that including the NVIX war-uncertainty measure in the list of predictors significantly improves out-of-sample forecast performance at a 12 months forecast horizon, where recursive estimates show that this improvement in forecast performance is largest in the first half of the sample period. In the second half of the 20th century, the predictive value of the war-related component relative to the other NVIX components has decreased. Furthermore, a dynamic extension of the BRT approach shows that, in addition to war-related uncertainty, various lags of government-related uncertainty enter the list of top predictors at a forecast horizon of 12 months. Recursive estimates show that the relative importance of this component of uncertainty is comparable to that of wars-related uncertainty, but also that it has experienced a noticeable drop since approximately 2000 at a forecast horizon of 12 months.

Our results concerning the relative importance of war- and (in the dynamic BRT approach) government-related uncertainty for recession forecasting at longer forecast horizons mirrors the finding reported by Manela and Moreira (2017) find that wars- and government-related uncertainty explain a substantial part of the time variation in stock-market risk premia. Moreover, our result that uncertainty helps to improve recession forecasts at a longer-term forecast horizon is similar to a result reported by Karnizova and Li (2014), who find that economic-policy uncertainty has significant predictive power for forecasting recessions at forecast horizons beyond five quarters. Our result differs from their result, however, in that we report, for the long sample period that we study, that a closer look at disaggregated components of uncertainy rather than economic-policy or government-related uncertainty per se helps to deepen our understanding of the role of uncertainty and its various dimensions for forecasting U.S. recessions.

We organize the remainder of this research as follows. In Section 2, we explain how our research relates to recent literature. In Section 3, we describe the BRT approach. We also describe how ROC curves can be used to evaluate forecast performance. In Section 4, we describe our data. In Section 5, we summarize our empirical results. In Section 6, we conclude.

2 Some remarks on the literature

In recent years, researchers have used various techniques to inspect the link between macroeconomic fluctuations and uncertainty. Karnizova and Li (2014) use Probit models to highlight the role of the news-based measure of uncertainty developed by Baker, Bloom, and Davis (2016) for forecasting U.S. recessions based, while Balcilar, Gupta, and Segnon (2016) emphasize the gains from using mixed-frequency Markov-switching models in forecasting U.S. recessions based on the same measure of uncertainty. Balcilar, Gupta, and Jooste (2017b) use bivariate long-memory models to show that this measure of uncertainty can also forecast U.S. inflation in an effective manner compared to short-memory models. Unlike the above mentioned three studies, which concentrate on post-World War II data, Segnon et al. (2018) forecast quarterly U.S. GNP over the period from 1900 to 2014 using various linear and nonlinear bivariate models featuring Baker, Bloom and Davis.'s (2016) news-based measure of uncertainty.[5] Finally, Junttila and Vataja (2017) show that inclusion of the Baker, Bloom, and Davis (2016) news-based measures of uncertainty for either the US, UK, or overall European economies improves the forecast ability of predictive regression models based on standard financial-market information, especially for the period before the 2008 global financial and real economy crisis.

Traditionally, variants of Probit/Logit models have been a major modeling device in the extensive and significant literature on forecasting recessions (e.g. Dueker, 1997; Estrella and Mishkin, 1998; Kauppi and Saikkonen, 2008; Nyberg, 2010; Ratcliff, 2013; among others). A disadvantage of the BRT approach relative to the kind of Probit/Logit models often used in that literature clearly is its relative computational complexity. The BRT approach, however, also has significant advantages relative to classic Probit/Logit models and other models widely studied in recent research on uncertainty and business-cycle fluctuations. The BRT approach uses a data-driven selection of predictors. Such a data-driven selection of predictors clearly is advantageous when a researcher does not have a strong prior for a specific economic theory of business-cycle fluctuations. Moreover, the BRT approach is a modelling platform that renders it possible to rigorously capture potential nonlinear links between the recession probability and the predictors and to shed light on interaction effects between predictors, where powerful techniques like partial-dependence plots make it possible to visualize such nonlinear and interaction effects.[6]

Recent empirical evidence suggests that modelling nonlinear and interaction effects is important. Caggiano, Castelnuovo, and Figueres (2017a) and Caggiano, Castelnuovo, and Pellegrino (2017b) find that an unanticapted increase in economic policy uncertainty has a statistically and economically larger effect on U.S. unemployment in recessions than in expansions (see also Caggiano, Castelnuovo and Groshenny, 2014). Foerster (2014) reports that an uncertainty shock, as measured in terms of a sudden increase in the VIX-index of stock-market volatility, produces a substantial decline in employment growth. In contrast, employment growth only slowly returns to its pre-shock level when uncertainty decreases in the following period, suggesting that some form of hysteresis effect may be at work. Pellegrino (2014) finds that monetary-policy shocks are much less powerful during times of high uncertainty (for an analysis of spill over effects of U.S. economic policy uncertainty on the effectiveness of Euro area monetary policy, see Balcilar et al. 2017a). Similarly, Pellegrino (2018) documents for the Euro area that the peak and cumulative effect of monetary policy shocks estimated by means of an Interacted-VAR model are lower during times of high uncertainty. Results reported by Ma, Olson, and Wohar (2018) based on U.S. data for the period from the mid 1980s to 2008 show that the Fed cuts the Federal Funds rate in response to increases in macroeconomic uncertainty. Caggiano, Castelnuovo, and Figueres (2017a) and Caggiano, Castelnuovo, and Pellegrino (2017b) use an Interacted-VAR model to argue that contractionary effects of uncertainty shocks are aggravated when monetary policy operates at the zero-lower-bound. Lensink and Murinde (2006), in turn, find for panel of UK firms that an inverted-U shaped function proxies the effect of uncertainty on corporate investment (for an analysis of how economic policy uncertainty in interaction with firm-level uncertainty effects firm-level investment, see Kang, Lee and Ratti, 2014). Such an inverted-U shaped function can arise in models of irreversible investment under uncertainty (Sarkar 2000). Hence, both available empirical evidence and theoretical considerations clearly show that nonlinear effects of uncertainty on the probability of a recession cannot be ruled out. Moreover, when there are different sources of uncertainty, as in our analysis, it is likely that these sources of uncertainty interact in a way such that the nonlinear link between uncertainty and recessions can become quite complex. The BRT approach is a natural candidate to model such complex nonlinearities and interaction effects.

In recent research, Ng (2014) uses a BRT approach to forecast U.S. recessions. Important findings are that the list of predictors that help to forecast recessions comprises less than 10 variables (including interest-rate variables), and that the relative importance of predictors has changed over time. Ng (2014) does not study the informational content of the NVIX and it components for predicting U.S. recessions. Moreover, her sample period runs from 1961:01 to 2011:12, whereas our sample period covers more than a century of monthly data. Its sheer length is an important feature of our data set given that recessions are relatively rare events. Other recent applications of boosting techniques in the context of business-cycle forecasting are Buchen and Wohlrabe (2011), who study the performance of boosting relative to other popular forecasting techniques with regard to predicting the growth rate of U.S. industrial production, and Robinzonov, Tutz, and Hothorn (2012), who apply boosting techniques to predict the monthly growth rate of German industrial production. Lehmann and Wohlrabe (2016) use boosting to predict German industrial production, and Wohlrabe and Buchen (2014) study the forecast performance of boosting with regard to several macroeconomic variables. Bai and Ng (2009) analyze the usefulness of boosting as a forecasting technique in the context of factor models, and they apply their techniques to forecast inter alia the growth rate of U.S. industrial production. Berge (2015) compares the predictive power of a linear and a nonlinear boosting model (but not boosted regression trees) with (equal, Bayesian) model-averaging techniques for the forecasting period from May 1985 to December 2013. Results show that Bayesian model averaging and the boosting model produce better forecasts of U.S. recessions than an unweighted model average, where the predictive value of predictors changes over time. Döpke, Fritsche, and Pierdzioch (2017) use the BRT approach to forecast recessions in Germany. They also briefly review other recent applications of boosting and regression trees in the economics and forecasting literature. They further use a "horse race" approach to show that the BRT approach shows a better out-of-sample performance than popular Probit models. While not at the center of our analysis, we also find that the BRT approach performs better than a simple Probit model. Still, as we have already mentioned, the main purpose of our analysis is to use the BRT approach to shed light on the predictive value of uncertainty and its components for recession forecasting. We, thereby, close a significant wedge in earlier research, given the prominence that various uncertainty measures have gained in recent research as factors that have the potential to significantly shape macroeconomic fluctuations.

Whilst economists have started only very recently to add machine-learning techniques to their portfolio of quantitative techniques, the BRT approach and related machine-learning technique have been widely applied in research on expert and intelligent systems to deepen our understanding of various important economic phenomena, especially in the field of finance (Alfaro, Gámez and Elizon, 2008; Hsu et al., 2016; Oztekin et al., 2016; among others). Within the field of expert and intelligent systems, however, applications of machine-learning techniques to study the sources of business-cycle fluctuations are relatively scarce.[7] The list of exceptions includes research by Diaz, Theodoulidis, and Dupouy (2016), who model and forecast interest rates during the phases of the business cycle, and Lin and Pai (2010), who use a fuzzy support vector regression model to forecast an index of the Taiwanese business cycle during a sample period from January 1998 to October 2008. Our research adds to this research in that we use the BRT approach to study U.S. recessions based on a comprehensive data set that extends back to 1889, where we pay special attention to the role of uncertainty for recession forecasting.[8]

3 Empirical methods

3.1 The mechanics of the BRT approach

We model recessions as a binary variable, $y_{t+h} \in \{0, 1\}$, where h = forecast horizon, $t = 1,\dots$ is a time index, and y_t = 1 denotes an event (that is, a recession) while $y_t = 0$ denotes a nonevent. Moreover, we define $\tilde{y}_{t+h} = 2y_{t+h} - 1$, such that $\tilde{y}_{t+h} \in \{-1, 1\}$, and we let $\mathbf{x_t} = (x_{t,1}, x_{t,2}, \dots)$, denote the predictors. The problem is to find a function, $F(\mathbf{x_t})$, of the predictors so as to minimize the expected value, E, of the following loss, $\mathcal{L}$, function (Friedman, Hastie and Tibshirani, 2000):

$$\mathcal{L}(F) = E \exp(-\tilde{y}_{t+h} F(\mathbf{x_t})), \tag{1}$$

The loss function decreases when the signs of $\tilde{y}_{t+h}$ and $F(\mathbf{x_t})$ are the same. It is straightforward to show that $\mathscr{L}(F)$ attains a minimum if $F(\mathbf{x_t})$ is set to one-half of the log-odds ratio (Friedman, Hastie and Tibshirani, 2000, 345):

$$F(\mathbf{x_t}) = \frac{1}{2}\log\frac{P(\tilde{y}_{t+h} = 1|\mathbf{x_t})}{P(\tilde{y}_{t+h} = -1|\mathbf{x_t})}, \tag{2}$$

where $P(\tilde{y}_{t+h} = 1|\mathbf{x_t})$ denotes the conditional recession probability. Hence, estimation of the function, $F(\mathbf{x_t})$, is equivalent to modeling the log-odds ratio. The latter can be modeled, in an initialization step, using the unconditional recession probability. In follow-up steps, boosting induces refined estimates of the function, $F(\mathbf{x_t})$, by partitioning this potentially complex function-approximation problem into a sequence of simple problems by assuming that $F(\mathbf{x_t})$ also known as the strong learner) can be expressed as the sum of simple weak learners, $T(\mathbf{x_t})$, as follow:

$$F(\mathbf{x_t}) = \sum_{m=0}^{M} T_m(\mathbf{x_t}), \tag{3}$$

where m = index of a weak learner and M = some upper bound on the number of weak learners. A gradient-descent boosting algorithm allows the weak learners to be estimated in a forward stage-wise way (Friedman 2001, Friedman 2002):

1. Start the algorithm by setting $F_0 = T_0 = \frac{1}{2}\log\frac{P(\tilde{y}_{t+h}=1)}{P(\tilde{y}_{t+h}=-1)}$.

2. Fix M. For m in $1:M$:

- **a.** Extract the negative gradient vector: $z_{t,m} = -\partial\mathscr{L}(F)/\partial F$.
- **b.** Fit a weak learner, $T_m(\mathbf{x_t})$, to $z_{t,\,m}$.
- **c.** Update the function estimate: $F_m(\mathbf{x}_t) = F_{m-1}(\mathbf{x}_t) + T_m(\mathbf{x_t})$ and go back to (a).

3. At $m = M$: $F_M(\mathbf{x}_t) = T_0(\mathbf{x_t}) + T_1(\mathbf{x_t}) + \ldots + T_M(\mathbf{x_t})$.

Our weak learners are regression trees. A regression tree recursively partitions in a binary hierarchical top-down way the predictor space into non-overlapping rectangular regions, where a region-specific constant is used for prediction at a terminal node. Every region is defined by a predictor selected for partitioning and the value of the predictor at wich a split is invoked, both of which are selected to minimize a quadratic loss function defined over the negative gradient vector and the region-specific constant prediction. Friedman (2002, Algorithm 1) shows that regression trees can be built into Step 2a of the gradient-descent boosting algorithm by fixing the terminal node responses, γ, such that

$$\gamma_{l,m} = \arg\min_{\gamma} \sum_{\mathbf{x_t}\in R_{l,m}} \mathscr{L}(F_{m-1}(\mathbf{x_t}) + \gamma), \tag{4}$$

Newton's method solves this minimization problem (Friedman, Hastie and Tibshirani, 2000, 353), and Equation (3) can then be rewritten as $F(\mathbf{x_t}) = \sum_{m=0}^{M} \gamma_{l,m}\mathbf{1}_{\mathbf{x_t}\in R_{l,m}}$, where $\mathbf{1}$ = indicator function, and R_l = the l non-overlapping rectangular tree regions.

Friedman (2001) proposes to use a shrinkage parameter, $0 < \lambda \le 1$, to reduce the influence of individual weak learners on the strong learner. Step 2c of the gradient-descent boosting algorithm then becomes $F_m(\mathbf{x_t}) = F_{m-1}(\mathbf{x_t}) + \lambda\gamma_{l,m}\mathbf{1}_{\mathbf{x_t}\in R_{l,m}}$. Finally, Friedman (2002) suggests to stabilize predictions by adding a stochastic element to Step 2a of the gradient-descent boosting algorithm. To this end, one samples without replacement a subset from the data and then uses only the sampled data to build the next weak learner.

3.2 Using ROC techniques to evaluate forecast performance

Like Berge and Jordà (2011), Liu and Moench (2016), Döpke, Fritsche, and Pierdzioch (2017), and Pierdzioch, Reid, and Gupta (2018), we apply ROC techniques to evaluate the performance of the BRT approach (for introductions, see Greiner, Pfeiffer and Smith, 2000; Baker and Kramer, 2007). To this end, we define a recession as an "event" (that is, $\tilde{y}_{t+h} = 1$), and a boom as a "nonevent" (in this case, we have $\tilde{y}_{t+h} = -1$). In order to trace out whether the BRT approach signals that a recession is gathering steam, we assume that a "signal" occurs whenever the estimated recession probability implied by the BRT approach exceeds some cutoff value, c: $\hat{P}(\tilde{y}_{t+h} = 1|\mathbf{x_t}) \geq c$. Similarly, the BRT approach gives a "nonsignal" whenever the estimated recession probability falls short of the cutoff value: $\hat{P}(\tilde{y}_{t+h} = 1|\mathbf{x_t}) < c$.

A ROC curve expresses the rate of true recession signals as a function of the rate of false recession signals for alternative cutoff values. The rate of true recession signals is also known as sensitivity, $SE(c)$, while the rate of false recession signals equals one minus specifity, where specifity, $SP(c)$, is defined as the ratio of true nonsignals relative to all non-recessions. Both sensitivity and specifity are functions of the cutoff value. When the cutoff value approaches zero, the sensitivity of the BRT approach converges to unity because it captures all recessions. At the same time, however, specificity converges to zero because the BRT approach does not send any correct nonsignals. Similarly, a very high cutoff value (that is, c converges to unity) implies that the BRT approach does not capture any recession, implying that sensitivity goes to zero. Specificity approaches unity because the approach correctly classifies all non-recessions.

As a result, if we let c vary in the interval [0, 1], we can compute a ROC curve that starts in a $[0, 1] \times [0, 1]$ unit quadrant with $1 - Sp(c)$ on the horizontal axis and $Se(c)$ on the vertical axis at the point [0, 0] and then increases until it reaches the point [1, 1]. If the performance of the BRT approach is indistinguishable from the performance of a pure noise signal for all cutoff values, then we have always $SE(c) = 1 - SP(c)$, resulting in a ROC curve that is identical with the bisecting line. The ROC curve lies above the bisecting line if the BRT approach outperforms a pure noise signal for all cutoff values, such that $SE(c) > 1 - SP(c)$ (except, of course, at the endpoints, where $SE(c) = 1 - SP(c)$). Conversely, if a pure noise signal always outperforms the BRT approach then $SE(c) < 1 - SP(c)$ for all cutoff values, giving rise to a ROC curve that lies below the bisecting line. In this case, reverting the definition of a signal again results in a ROC curve that settles above the bisecting line. Finally, a ROC curve can cross the bisecting line if the performance of the BRT approach relative to a pure noise signal depends on the choice of the cutoff value, that is, if $SE(c) < 1 - SP(c)$ for some cutoff values and $SE(c) > 1 - SP(c)$ for others.

The area, AUROC, under a ROC curve is a summary statistic of the performance of the BRT approach. If the BRT approach gives perfect recession forecasts (such that the resulting ROC curve approaches the upper-left corner of the unit quadrant) then AUROC =1. If the recession forecasts implied by the BRT approach mimick a pure noise signal, in which case the ROC curve coincides with the bisecting line, we have AUROC = 0.5. In intermediate cases, when the BRT approach outperforms a pure noise signal but does not imply perfect forecasts, then AUROC > 0.5. A larger AUROC statistic, thus, signals a better performance of the BRT approach. Estimation of the AUROC statistic can be done by adopting a non-parametric approach that uses the result that the AUROC statistic is linked to the Wilcoxon-Mann-Whitney U statistic (Bamber, 1975; Hanley and McNeil, 1982). We have (see the introductory review by Greiner, Pfeiffer and Smith, 2000, 38–39)

$$AUROC = \frac{n_0 n_1 - U}{n_0 n_1}, \tag{5}$$

where n_0 = # nonevents, n_1 = # events, and $U = R - 0.5\, n_0(n_0 + n_1)$ = two-sample Mann-Whitney rank-sum test with R = rank sum of the nonevents. The standard error of the AUROC statistic is given by (see Hanley and McNeil, 1982; Greiner, Pfeiffer and Smith, 2000)

$$SE = \sqrt{\frac{A + B + C}{n_0 n_1}}, \tag{6}$$

where $A = AUROC\ (1 - AUROC)$, $B = (n_1 - 1)\ (Q_1 - AUROC^2)$, $C = (n_0 - 1)\ (Q_2 - AUROC^2)$, with $Q_1 = AUROC/(2 - AUROC)$ and $Q_2 = 2\ AUROC^2/(1 + AUROC)$.

4 The data

We study monthly data from January 1889 to February 2017. We measure recessions as a binary 0/1-variable based on the NBER classification of economic cycles.[9] Because the NBER typically announces recessions with a delay, we essentially predict future months that the NBER will eventually classify as recessions. We study three forecast horizons: 3, 6, and 12 months (see also Dueker, 1997; Ng, 2014 argues that 3 months probably is the minimum recognition lag for recessions; see also Section 5.7 and the Supplementary Material). We construct the data such that we have the same number of observations for all three forecast horizons (the last forecast is made in 2016).

The NVIX components are taken from Manela and Moreira (2017).[10] The news data set includes the title and abstract of all front-page articles of the Wall Street Journal. Manela and Moreira (2017) focus on front-page titles and abstracts in order to ensure feasibility of data collection, and also because these are manually edited and corrected following optical character recognition, which in turn, improves their earlier sample reliability. The NVIX data is found to peak during stock market crashes, times of policy-related uncertainty, world wars, and financial crises. The reader is referred to Manela and Moreira (2017) for further details, who also discuss how they decompose the aggregate NVIX into its components. The comparative advantage of the NVIX stems from the fact that it is decomposed into different news sources and events that can affect the economy. In particular, the NVIX constituent components capture uncertainty stemming from (with the words searched for in brackets) government policy (tax, money, rates, government, plan), intermediation (banks, financial, business, bank, credit), natural disaster (fire, storm, aids, happening, shock), securities markets/stock markets (stock, market, stocks, industry, markets), and wars (war, military, action,world war, violence). There is also available data for an "unclassified" component (U.S., special, Washington, treasury, gold).

In addition to the NVIX components, we include several other widely-studied predictors of recessions in our list of predictors. Naturally, availability of data back to 1889 also governs our choice of predictors. Our list of predictors includes the term spread (10-year government bonds – short-term interest rate), a short-term interest rate, the inflation rate (year-on-year change in the consumer price index), real stock market return (year-on-year change in the S&P500 index; continuous compounding), the price-dividend and price-earnings ratios, real oil-price returns (year-on-year change in the price of oil; West Texas Intermediate; the data comes from the Global Financial Database; continuous compounding), and returns on the real dollar-pound exchange rate (computed using consumer-price indexes; continuous compounding).[11] In addition, we include absolute stock-market returns, absolute oil-price returns, and absolute real exchange-rate returns as measures of stock-market, terms-of-trade, and commodity-price volatility in the list of predictors. Absolute returns are a simple measure of the realized volatility of these predictors and proxy uncertainty stemming from stock-market, oil-price, and real exchange-rate returns fluctuations.[12]

5 Empirical results

5.1 Calibration issues

We coded up all scripts that we used to compute the empirical results reported in this research in the R programming environment for statistical computing (R Development Core Team 2015). In addition to several purpose-written scripts, we use the add-on package "gbm" (loss function "Adaboost", Ridgeway 2015). We set the minimum number of observations per terminal node to 5 and the shrinkage parameter to $\lambda = 0.1$. We select 50% of the training data at random in every step of the recursion that generates an ensemble of weak learners. Like Ng (2014), we consider simple "stumps" as base learners.[13]

In Sections 5.2–5.4, we use 70% of the data (sampled without replacement) to train the BRT approach, and the remaining 30% (that is, roughly the usual bootstrap proportion) to asses its fit, to study the relative importance of variables, and to compute confidence bands for marginal effects (see also Döpke, Fritsche and Pierdzioch, 2017). We repeat this process 1000 times, where we use five-fold cross validation to trace out the optimal number of weak learners in every simulation run. The maximum number of weak learners is fixed at $M = 3000$, but the cross-validated optimal number of weak learners is typically much smaller. In Sections 5.5–5.7, we study recursive estimates of the BRT approach and their implied forecasts to shed light on the out-of-sample forecast performance of the BRT approach.

5.2 Properties of the BRT approach

We illustrate in Figure 1 some of the properties of the fitted BRT approach. We plot, for the three forecast horizons being studied, the sampling distribution of the optimal cross-validated number of weak learners along with some summary statistics. Depending on the forecast horizon being studied, the BRT approach builds the function $F_m(\mathbf{x_t})$ from ensembles of (on average) roughly 200–300 weak learners.

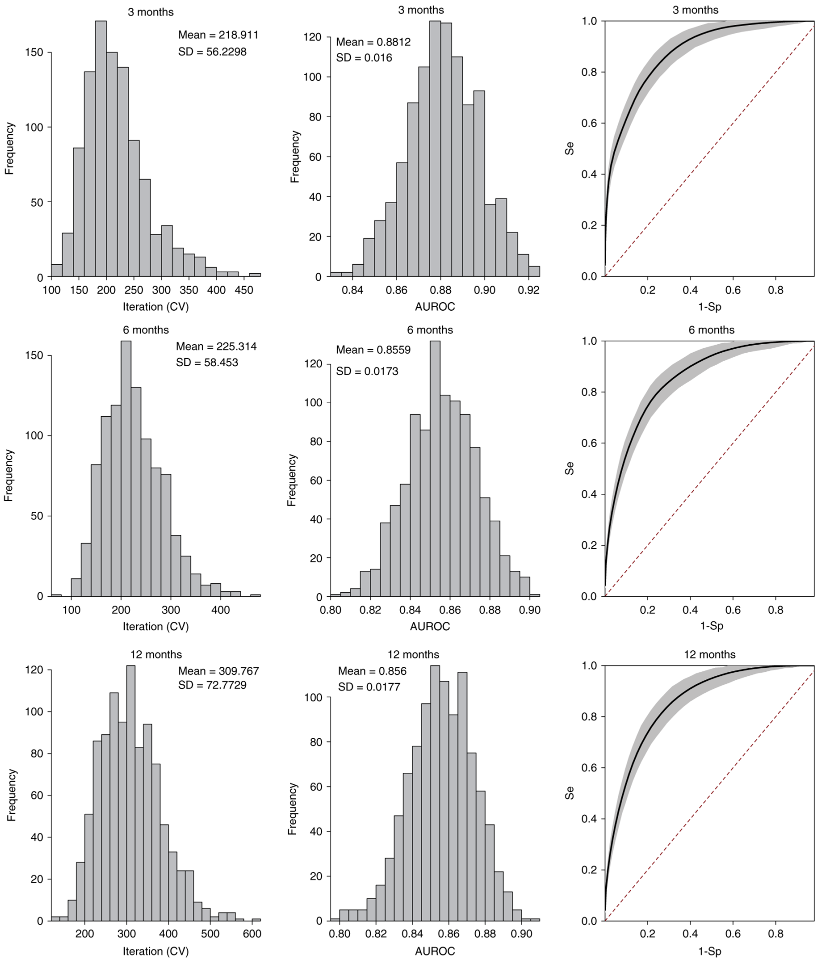

Figure 1: Properties of the BRT approach.
Results are based on 1000 simulation runs (see Section 5.1 for details). Shaded areas denote the simulated 95% confidence intervals of the ROC curves. SD = standard deviation.

We further use the simulation results to study the fit of the BRT approach. To this end, we plot ROC curves along with the simulated 95% confidence band. We also plot the simulated sampling distribution of the corresponding AUROC statistics and some summary statistics. For every single one of the 1000 simulation runs, we compute the AUROC statistic using the 30% test fraction of the data. Two results emerge. First, the AUROC statistics typically assume values well-above 0.80, where the simulated 95% confidence intervals range from 0.85 to 0.91 (0.82–0.89, 0.82–0.89) for a forecast horizon of 3 (6, 12) months. Henc, the fit of the BRT approach clearly is significantly better than that of a pure noise signal. Second, as one would have expected, the mean of the AUROC statistic decreases as the forecast horizon increases, where the decrease is comparatively larger when we switch from a forecast horizon of 3 months to a forecast horizon of 6 months.

5.3 Relative importance of predictors

Figure 2 shows, for the three forecast horizons under consideration, the relative importance of the various predictor variables. The relative importance of a predictor is measured in terms of the the sum over nonterminal nodes of the squared improvement resulting from using a predictor to form tree splits (Breiman et al. 1984). This measure can easily be adapted to measure relative importance of a predictor in case of the BRT approach by averaging across boosted regression trees (Friedman 2001) and, in case of our simulation experiment, by averaging across the 1000 simulation runs.

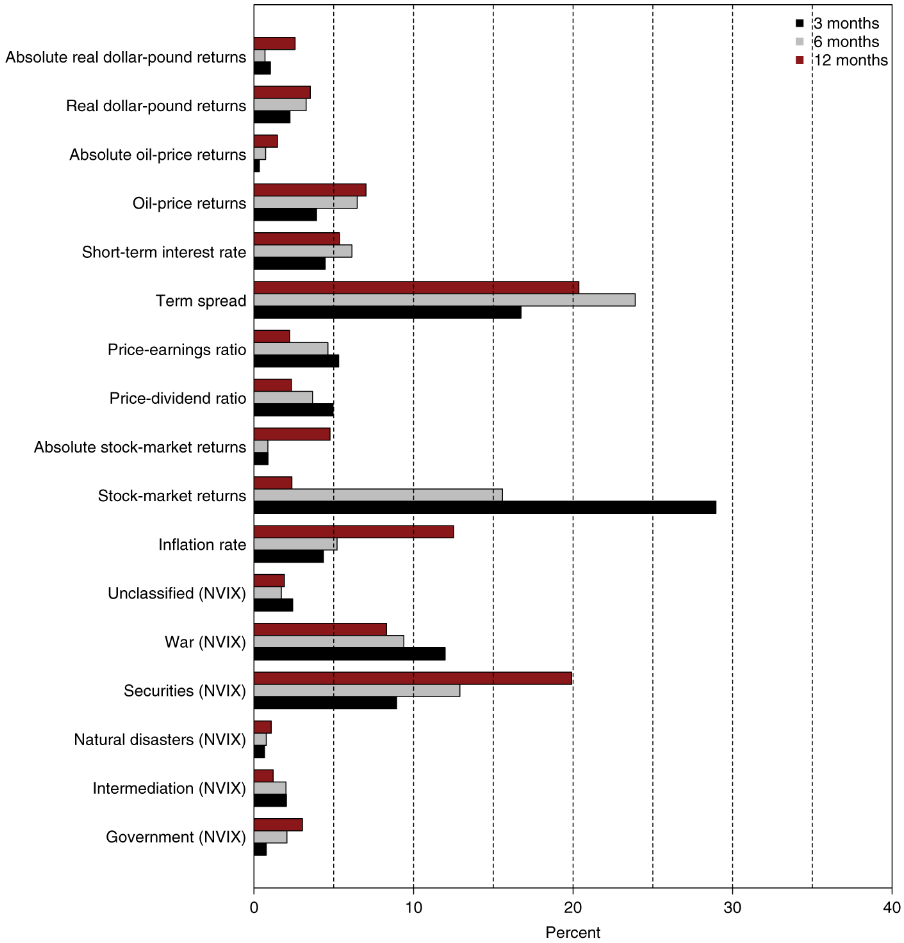

Figure 2: Relative importance of predictors.
Relative importance is averaged over 1000 simulation runs (see Section 5.1 for details).

The top five predictors of U.S. recessions are stock-market returns, the term spread, the inflation rate, and the two NVIX components that summarize war concerns and uncertainty stemming from securities-markets developments. There are, however, noticable differences across forecast horizons. The relative importance of stock-market returns shrinks from almost 30% to below 5% as the forecast horizon becomes longer. In line with earlier research (Estrella and Mishkin, 1998; Dueker, 1997; Nyberg, 2010 finds that the term spread performs best at a lag of 6 months), the importance of the term spread and the inflation rate increases (to above 20% and somewhat below 15%, respectively) as we move from a forecast horizon of 3 months to a forecast horizon of 12 months. Similarly, the relative importance of the NVIX component that summarizes war-related uncertainty decreases somewhat at the long forecast horizon (hovering around 10%), while the relative importance of the NVIX component that captures securities-markets uncertainty increases to approximately 20%.

The relative importance of stock-market returns at a short forecast horizon corroborates results reported by Estrella and Mishkin (1998), who also emphasize the informational content of the slope of the yield curve for forecast horizons beyond one quarter. For empirical findings that shed light on the predictive value of the yield curve, see also, for example, Estrella, Rodriguez, and Schich (2003) and Rudebusch and Williams (2009). Bluedorn, Decressin, and Terrones (2016) document, using data for the G-7 countries, that decreases in asset prices, and especially decreases of real equity prices, foreshadow recession starts. They also find that increased equity-market uncertainty, as measured in terms of the implied/realized S&P volatility, has predictive value for recession starts. Barro and Ursuá (2017) report that stock-market crashes forecast depressions, especially in periods of currency or banking crises.

5.4 Marginal effects

Figure 3–Figure 5 plot for the three different forecast horizons the marginal-effect curves of the predictors. The marginal-effects curves visualize the effect of a predictor on the probability of a recession (measured at the log-odds scale). The influence of the other predictors is captured by means of the weighted-traversal technique described by Friedman (2001). The shaded areas are the simulated 95% confidence intervals.

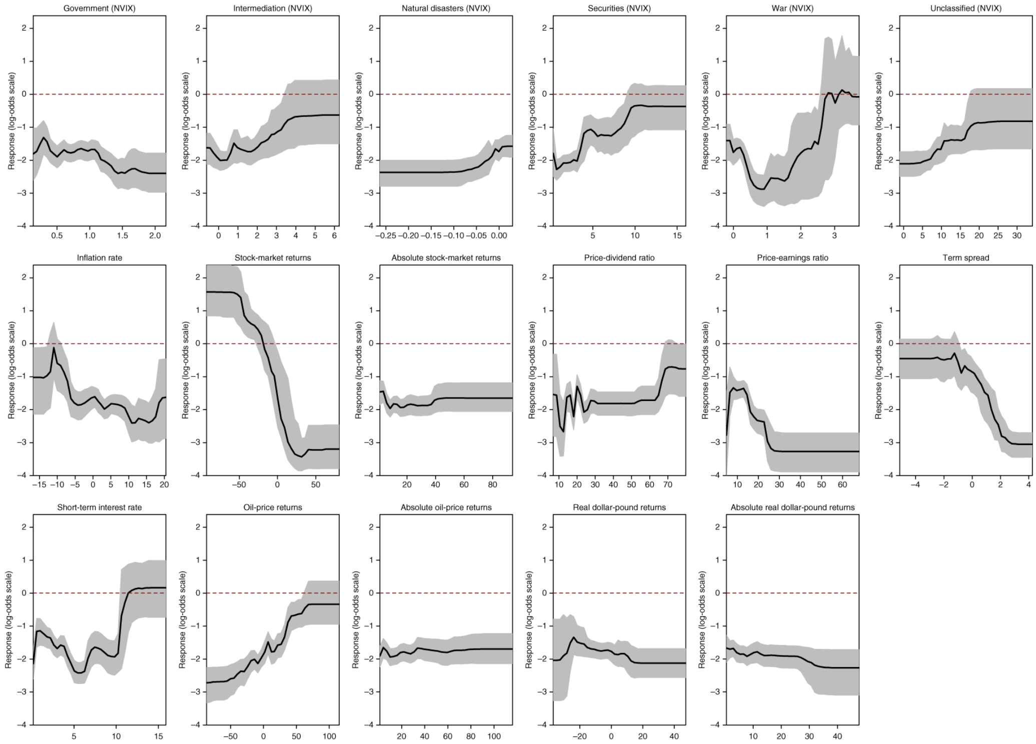

Figure 3: Partial dependence (3-months-ahead forecasts).
Results are based on 1000 simulation runs (see Section 5.1 for details). Horizontal axis = mean per quantile of 2.5% width of the leading indicators computed across 1000 simulation runs. Thick line = mean per quantile of the log-odds ratio computed across simulation runs. Shaded area = 95% confidence interval computed for every quantile.

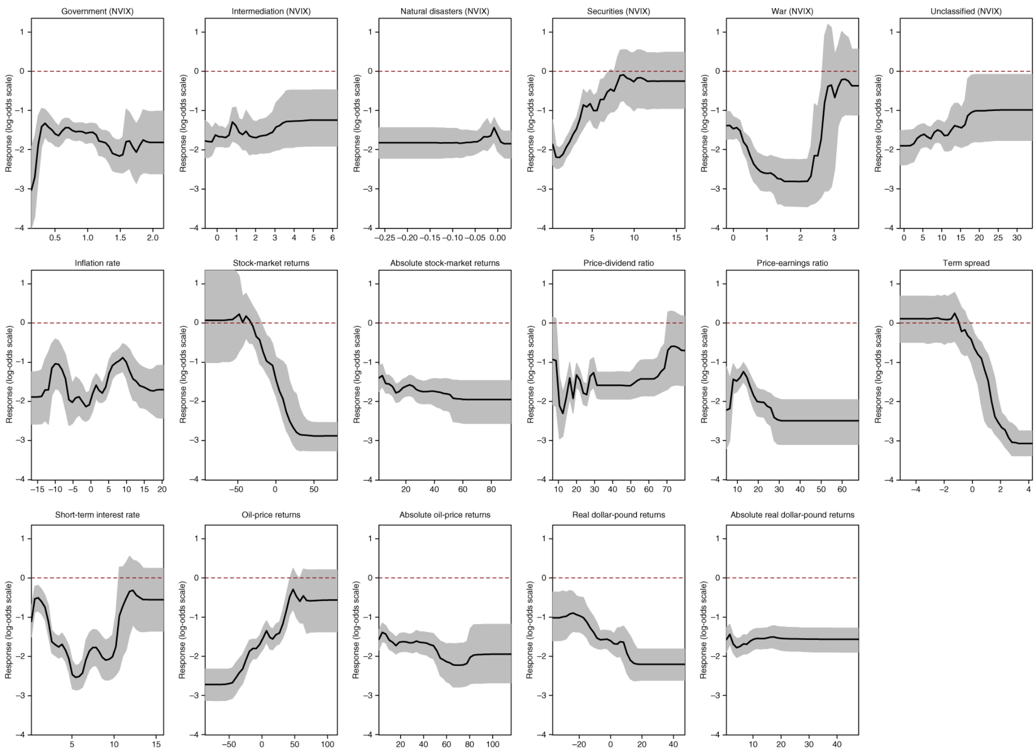

Figure 4: Partial dependence (6-months-ahead forecasts).
Results are based on 1000 simulation runs (see Section 5.1 for details). Horizontal axis = mean per quantile of 2.5% width of the leading indicators computed across 1000 simulation runs. Thick line = mean per quantile of the log-odds ratio computed across simulation runs. Shaded area = 95% confidence interval computed for every quantile.

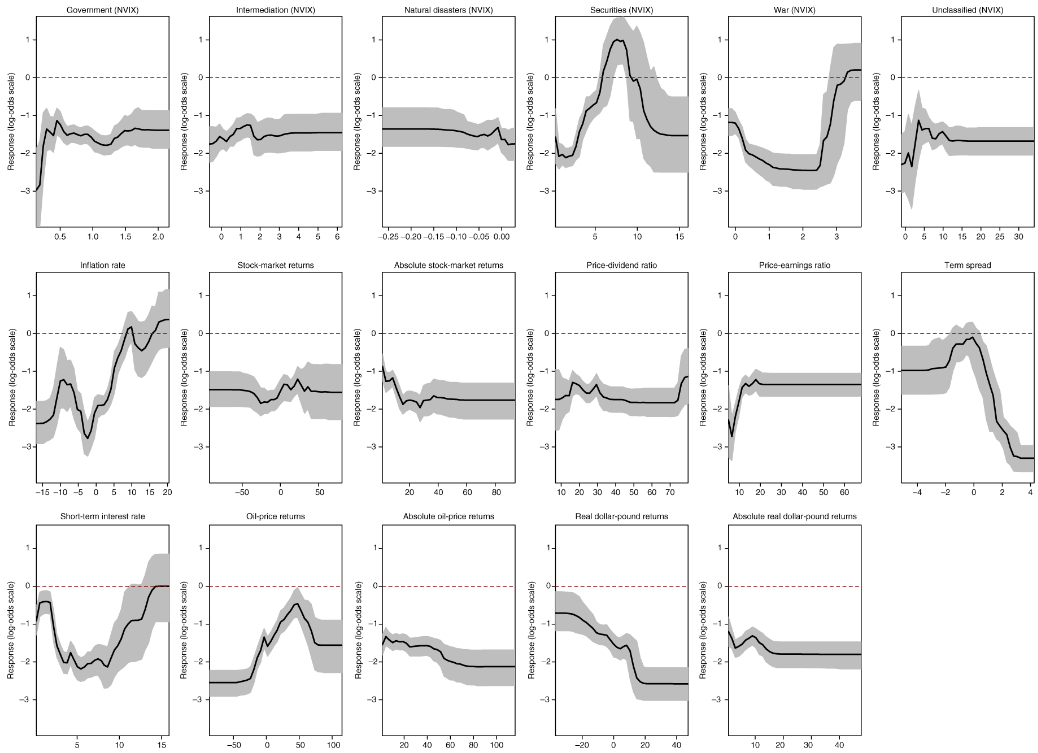

Figure 5: Partial dependence (12-months-ahead forecasts).
Results are based on 1000 simulation runs (see Section 5.1 for details). Horizontal axis = mean per quantile of 2.5% width of the leading indicators computed across 1000 simulation runs. Thick line = mean per quantile of the log-odds ratio computed across simulation runs. Shaded area = 95% confidence interval computed for every quantile.

The marginal-effect curves show that, at all three forecast horizons, the recession probability sharply decreases in the region where the term spread switches sign from negative to positive. The recession probability also abruptly increases as the short-term interest rate reaches a level of about 10%. Increases in the price of oil, as indicated by positive oil-price returns, lead to an increase in the recession probability (but we also observe a noticeable nonlinear effect for a forecast horizon of 12 months). The recession probability decreases in the returns of the real exchange rate, where this decrease is more pronounced at the two longer forecast horizons. An increase in the inflation rate signals a higher recession probability, but only at a forecast horizon of 12 months.

As for the NVIX components, the recession probability increases in the component that measures war-related uncertainty, where this effect is more precisely estimated for the two longer forecast horizons. The marginal-effects curves also demonstrate that this effect is highly nonlinear. Such a stark nonlinearity can also be observed in case of the NVIX component that summarizes uncertainty regarding securities-markets developments, mainly for a forecast horizon of 12 months. At the two shorter forecast horizons, an increase in this NIVX component tends to signal an increase in the recession probability, where the marginal-effects curves reach a plateau that is surrounded by relatively wide confidence bands for large realizations of the securities-markets component. The marginal-effects curves of the other NVIX components show no clear-cut pattern and are in the majority of cases more or less flat, where an increase in the recession probability increases in the "unclassified" component at forecast horizons of 3 and 6 months. This effect, however, is estimated relatively imprecisely as indicated by the wide confidence bands in the corresponding region of the marginal-effects curves.

5.5 Recursive estimates of relative importance

Because our sample period covers more than a century of monthly data, we next present results based on recursive estimates of the BRT approach.[14] To this end, we use data up to and including 1899/12 to initialize the estimations. We then add 1 month of data, reestimate the BRT approach, and recursively continue in this way until we reach the end of the sample period.

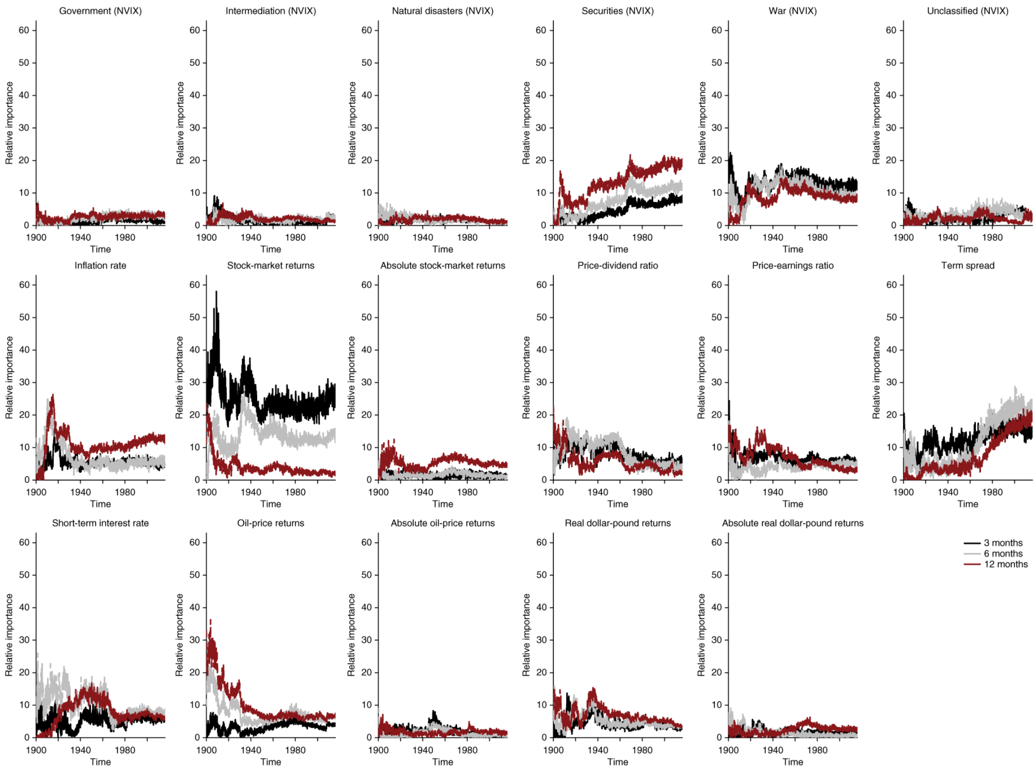

Figure 6: Recursively estimated relative importance.
Initial estimates of the BRT approach use data up to and including 1899/12. The BRT approach is then estimated on a recursively expanding estimation window by adding step-by-step 1 month of data until the end of the sample period is reached.

Figure 6 plots the recursively estimated relative importance of the predictor variables. For the majority of predictors, the relative importance of the predictors has stayed more or less stable over time. There are, however, exceptions. Results show that the relative importance of the term spread has increased since the 1960s. A mirror-image of this increase is that the relative importance of the short-term interest rate has decreased since the 1960s. The relative importance of stock-market returns peaked before 1920 and experienced another noticeable increase in the 1930s. Since then, it has stayed relatively stable at all three forecast horizons. Similarly, the relative importance of the NVIX component that concerns war-related uncertainty has stayed relatively stable over time within an interval of approximately 10%–20% (except at the very beginning of the sample period when we start the recursion). In contrast, the relative importance of the NVIX component that summarizes uncertainty from securities-markets developments has increased over time, especially at a forecast horizon of 12 months. Figure 6 further shows that the relative importance of oil-price movements has substantially decreased over time at forecast horizons of 6 and 12 months, and has stayed relatively stable since the 1940s at approximately 10% for all three forecast horizons.

5.6 Uncertainty and out-of-sample forecasts

We next use the recursive estimates of the BRT approach to analyze the out-of-sample forecast performance of the BRT approach. To this end, we compare the AUROC statistics implied by the baseline specification that excludes all NVIX components from the list of predictors with a specification that features all predictors of the baseline model plus all NVIX components. This comparison sheds light on the incremental contribution of the NVIX components to the out-of-sample forecast performance of the BRT approach.[15]

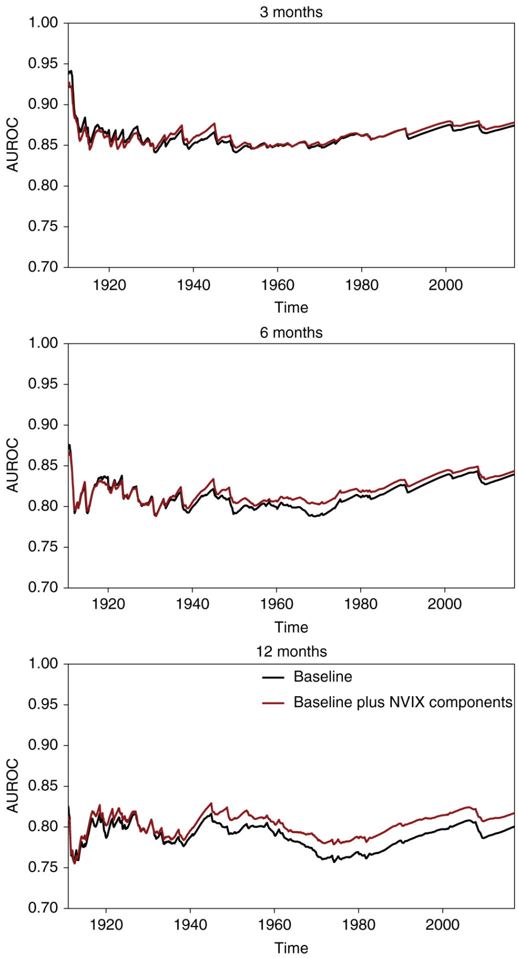

Figure 7: Recursively estimated out-of-sample AUROC statistics.
Initial estimates of the BRT approach use data up to and including 1899/12. The BRT approach is then estimated on a recursively expanding estimation window by adding step-by-step 1 month of data until the end of the sample period is reached. The first 10 years of forecasts generated in this way are then used to compute an initial estimate of the AUROC statistic. The estimation window is then recursively expanded by adding step-by-step 1 month of data until the end of the sample period is reached.

Figure 7 plots recursive estimates of the AUROC statistic for the two specifications. The differences between the two specifications are small for a forecast horizon of 3 months, where the baseline specification even performs slightly better thn the extended specification until around 1940. The differences between the two specifications are larger when we switch to forecast horizons of 6 and 12 months. In particular, the specification that features the NVIX components starts to dominate the baseline specification in terms of out-of-sample performance after approximately 1940. On balance, the second specification (the one with the NVIX components) clearly outperforms the baseline specification (the one without any NVIX components) in case the forecast horizon is 12 months.

We also tested formally the hypothesis that the difference between the out-of-sample AUROC statistics implied by the different specifications of the BRT approach is zero.[16] For forecast horizons of 3 and 6 months, the test results show that the differences between the AUROC statistics are not significantly different from zero. For a forecast horizon of 12 months, the null hypothesis of no difference between the AUROC statistics of the baseline specification and the AUROC statistics that features the NVIX components, on the other hand, can be rejected.

5.7 Modeling dynamics

The results we report in Sections 5.3–5.6 neglect that lagged values of the predictors may have predictive value for recessions. In order to capture potential lagged effects of the predictors, we add for every predictor twelve lags to the list of predictors. We also add twelve lags of the recession indicator (but exclude the contemporaneous recession indicator) to control for potential side effects of the persistence of recessions (and non-recessions) on the predictive power of the predictors.

Adding lagged recession indicators to the model brings to the forefront two modeling issues. A first modeling issue concerns the fact that a researcher can account for the persistence of recessions in different ways. Using the lagged recession indicator to this end is only one possibility. Another possibility is to use the lagged recession probability implied by the forecasting model. Yet another possibility is to use a combination of the lagged recession indicator and lagged recession probabilities (for an in-depth analysis, see Kauppi and Saikkonen, 2008).[17] The second modeling issue concerns the fact, already mentioned in Section 4, that the NBER publishes its recession indicator with a delay, resulting in a publication lag. A publication lag, in turn, leads to the question as to when a forecaster can use in practice the NBER recession indicator for making a recession forecast. Nyberg (2010) assumes a publication lag of 9 months. Kauppi and Saikkonen (2008) assume a publication lag of four quarters. The effective publication lag, however, may be shorter than nine or 12 months. Dueker (1997) argues that, while the NBER may not have officially announced a business-cycle turning point at a lag of 3 months, people likely have gathered enough information to gauge that the economy is in a recession.[18]

We next treat the lagged recession indicator as an instrument to control for the persistence of recessions when assessing the relative importance of the other predictors in general and the uncertainty measures in particular for forecasting recessions.[19] We focus on the third specification (the one that features all predictors of the baseline model and all NVIX components). In total, the dynamic BRT approach features 233 predictors.[20] We recursively estimate the dynamic BRT approach as described in Section 5.5.

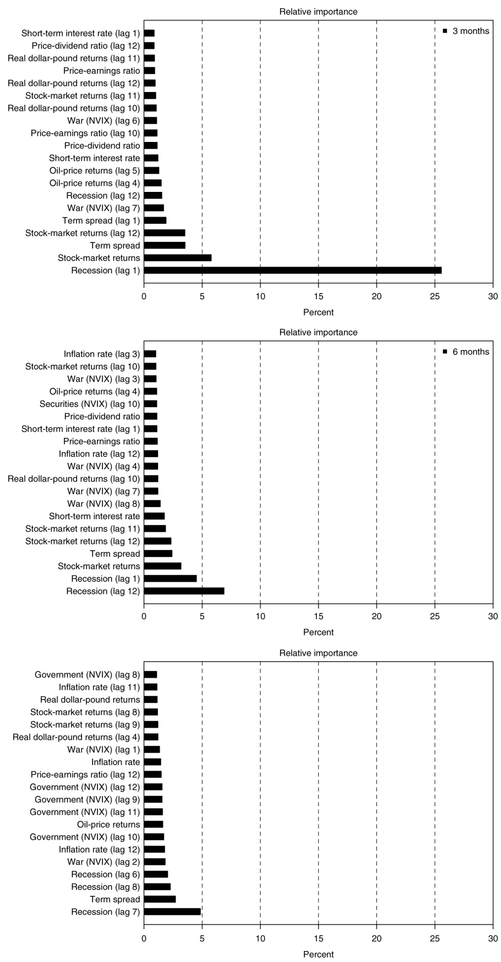

Figure 8: Relative importance of predictors in the dynamic model (averaged across time).
Relative Importance is averaged over recursive estimates of the BRT approach. Initial estimates of the BRT approach use data up to and including 1899/12. The BRT approach is then estimated on a recursively expanding estimation window by adding step-by-step 1 month of data until the end of the sample period is reached.

Figure 8 shows the relative importance of the top 20 predictors, where relative importance is averaged across the recursive estimates of the BRT approach. As expected, the relative importance of the recession indicator (lag 1) is strongest for a forecast horizon of 3 months, but it decreases when the forecast horizon is expanded to 6 months and 12 months. At all three forecast horizons, the list of top predictors features various lags. Interestingly, the government-component of the NVIX shows up with several lags in the top-20 list when the forecast horizon is 12 months. Again, stock market returns and the term spread are among the top predictors.

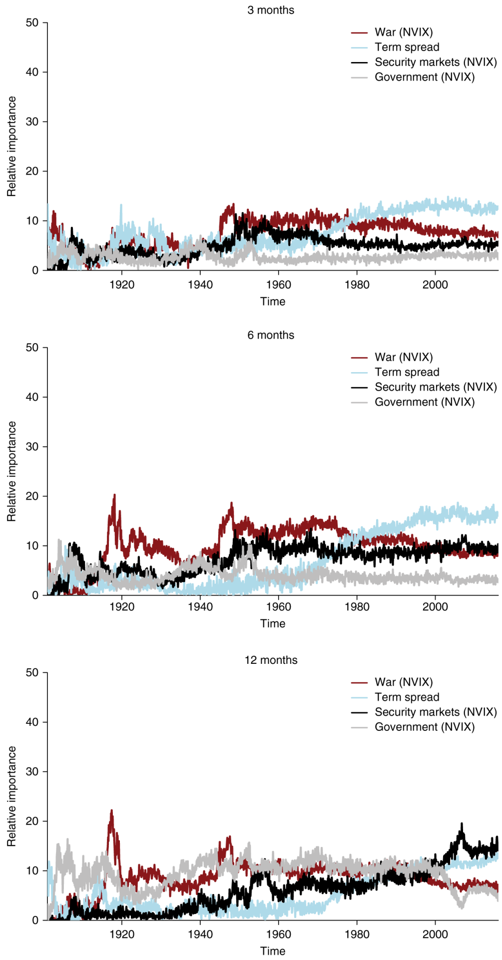

Figure 9: Relative importance of predictors in the dynamic model (aggregated for predictors).
Relative Importance is aggregated for contemporaneous and lagged predictors. Initial estimates of the BRT approach use data up to and including 1899/12. The BRT approach is then estimated on a recursively expanding estimation window by adding step-by-step 1 month of data until the end of the sample period is reached.

Figure 9 shows the evolution of relative importance over time, where we aggregate across the contemporaneous and lagged values of a predictor. We focus on the the term spread and the war- and securities markets-related components of uncertainty. In addition, we present results for government-related uncertainty because this NVIX component shows up in the list of top predictors with various lags when the forecast horizon is 12 months. The general pattern that emerges resembles the pattern already known from Figure 6. The relative importance of the term spread (and its lagged values) has increased after approximately 1960 and the relative importance of war-related uncertainty has fluctuated over time between approximately 10% and 20% (where it is relatively more important for the long forecast horizons). The relative importance of securities-markets-related uncertainty has increased in the second half of the sample period, where the increase is less pronounced than in Figure 6. Finally, the relative importance of government-related uncertainty increases as the forecast horizon becomes longer, a result that mirros that several of the lagged values of this NVIX component are included in the list of top predictors in Figure 8 (forecast horizon 12 months). The relative importance of government-related uncertainty is comparable to that of wars-related uncertainty at a forecast horizon of 12 months, and it shows a noticeable decline since approximately 2000.

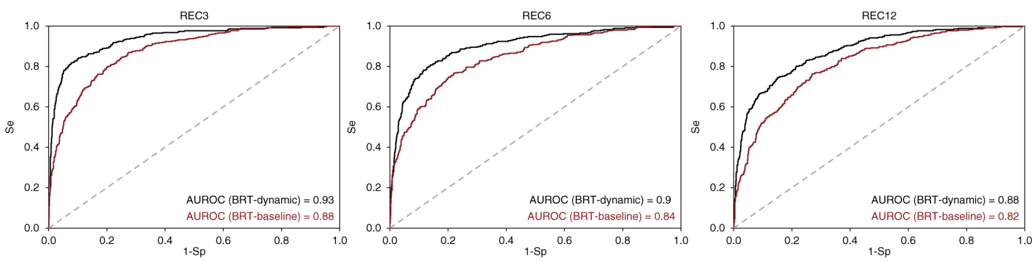

Figure 10: Comparison of the baseline BRT approach and the dynamic model.
Initial estimates use data up to and including 1899/12. The baseline and the dynamic model are then estimated on a recursively expanding estimation window by adding step-by-step 1 month of data until the end of the sample period is reached. The list of predictors includes all NVIX components.

Figure 10 shows the ROC curves and the corresponding AUROC statistics for the baseline model (without dynamics) along with the corresponding ROC curves and AUROC statistics for the dynamic model. The list of predictors includes all NVIX components. Results show that accounting for dynamics further improces the out-of-sample forecasting performance of the BRT approach. The AUROC statistics increase at all three forecasting horizons by about 0.06 as we move from the static to the dynamic model.

6 Concluding remarks

We have applied a BRT approach to shed light on the role of disaggregated uncertainty measures for forecasting U.S. recessions. Upon using more than a century of monthly data, and controlling for the influence of several other popular predictors of recessions, we have used ROC techniques to show that the NVIX component that summarizes war-related uncertainty helps to improve the out-of-sample performance of the BRT approach at the longer forecast horizons. An analysis of the relative-importance of predictors has revealed that wars-related uncertainty and securities-markets-related uncertainty are among the top five predictors of recessions. In the second half of the sample period, the NVIX component that concerns uncertainty regarding the state of securities markets has gained in relative importance. Similarly, the impact of the wars-related component of the NVIX on the out-of-sample forecast performance of the BRT approach is comparatively stronger until approximately the early 1980s (where the details of this timing somewhat depend on the calibration and the out-of-sample metric being studied), while since then the contribution of the other NVIX components to the predictive value of out-of-sample forecasts has strengthened. Inspection of marginal-effect curves has recovered that the probability of a recession is nonlinearly linked to war-related and securities-market uncertainty. Finally, estimation results for a dynamic BRT approach have revealed that, in addition to war-related uncertainty, lags of government-related uncertainty show up in the list of top predictors at a forecast horizon of 12 months, where the result that the relative importance of government-related uncertainty has declined in the last decade of the sample period deserves further scrutiny in future research.

Our paper adds to the widely available recent empirical evidence of the in-sample impact of uncertainty (see for example, Gupta, Lau and Wohar, 2019; Gupta et al., 2018, for a detailed literature review). We highlight the fact that, while there is no guarantee that in-sample predictability carries over to the out-of-sample predictability, the importance of uncertainty can be of such a degree that predictability translates into forecasting gains, even when controlling for a wide-array of possible leading indicators. In addition, we highlight the fact that it is important to categorize the types of uncertainty, as each of them plays an important role at various points in time, over and above conventional measures of financial-market turbulence. In other words, not only is uncertainty resulting from stress in financial markets important, but so are policy-related uncertainty and also geopolitical risks associated with wars. This is in line with the fact that financial and policy uncertainties do not necessarily comove together (Kostka and Roye, 2017). This evidence is important, since if we had not disaggregated uncertainty, we would have not be able to understand the role of a particular type of uncertainty at a specific point in time. Clearly, this information is of tremendous importance to policymakers, who plan to seize and implement policy measures and who, in turn, need information regarding which form of uncertainty is most important for the state of the economy when a policy decision has to be reached.

Our empirical analysis can be extended in several directions. One direction for future research is to study the predictive power of disaggregated uncertainty measures for recessions in other countries. Another direction for future research is to study the predictive power of disaggregated uncertainty for other macro variables like, for example, employment and investment. In this regard, it is interesting to bring together disaggregated uncertainty measures with disaggregated economic data (for state-level analysis of uncertainty on economic outcomes, see Mumtaz, Sunder-Plassmann and Theophilopoulou, 2018; for a state-level analysis of uncertainty and housing-market developments, see Christidou and Fountas, 2018). Such a disaggregated analysis can be particularly interesting with respect to wars-related uncertainty because, for example, the effects of this specific dimension of uncertainty may by more readily felt in states whose economic performance heavily depends on the health of the defense industry. It also is important to emphasize that we have been agnostic in our forecasting experiments about any specific channels through which uncertainty affects economic fluctuations. In future research, it is interesting to inspect such potential channels in more detail and to link, for example, wars- and government-related uncertainty to results documented in the literatures on the impact of wars and violent conflicts on trade flows (see, for example, Anderton and Carter, 2001; Blomberg and Hess, 2006) and the interplay of war threats and government investment in education (Aghion et al. 2014)

Finally, the recent U.S subprime crisis and the ensuing "Great Recession" have brought back to the forefront the fundamental insight that recessions and developmens in financial markets are deeply intertwined and that, in fact, the "health" of the financial system and of financial-market conditions are crucial for understanding business-cycle fluctuations. The renewed interest in the links between macroeconomic and financial conditions could set the stage to explore in future research further applications of boosted regression trees and other machine-learning techniques. In particular, given that researchers have used classification trees for financial-crises modeling (Manesse and Roubini, 2009), a natural next step is to build on our research and to use multivariate regression trees (for a recent application in a forecasting context, see Behrens, Pierdzioch and Risse, 2018) to explore whether and, if so, to which extent the disaggregated uncertainty measures that we have studied in our research are useful for the joint modeling and forecasting of both recessions and financial crises.

Funding

Deutsche Forschungsgemeinschaft. Funder ID: http://dx.doi.org/10.13039/501100001659 (Grant number: 275693836)

Notes

1 The uncertainty literature has mushroomed in recent years. For some further contributiosn, see Jones and Olson (2013, 2015) , Nodari (2014), Ludvigson, Ma, and Ng (2015), and Caldara et al. (2016), and Gupta, Lau, and Wohar (2019).
2 Baker, Bloom, and Davis (2016) and Larsen (2017) have also developed disaggregated measures of uncertainty, but their data starts only from 1985 to 1989.
3 It must, however, be pointed out that (unreported) results by Karnizova and Li (2014) also highlight the ability of the uncertainty index in predicting U.S. recessions over a long-span from 1900 to 2014, but this predictive analysis is in-sample-based. Their out-of-sample analysis covers the period of time around the Great Recession, i.e. 2006:Q1–2013:Q1, with an in-sample period from 1985:Q1 to 2005:Q4.
4 To be precise, the BRT approach shows that the log-odds ratio is a nonlinear function of the predictors. We often use the less technical phrase that the recession probability is linked in a nonlinear way to the predictors.
5 They show that, while a Markov-switching time-varying-parameter vector autoregressive (MS-TVP-VAR) model in most cases cannot be outperformed by its competitors when point forecasts are being studied, a Bayesian VAR (BVAR) model with stochastic volatility is the best-performing model in the majority of the cases for density forecasts.
6 It should be mentioned that one could also use a data-driven approach to forecasts recessions by means of standard Probit/Logit models by estimating, for example, such models on all possible combinations of predictors and then computing a forecasts from the best fitting model. Alternatively, one could an averaging scheme to combine the forecasts from the resulting large number of models. In doing so, however, one does not take into account the advantages of the BRT approach and, in fact, Döpke, Fritsche, and Pierdzioch (2017) show that the BRT approach performs better than such alternatives. For an example of a data-driven Probit-based approach to forecasting recessions, see Section the Supplementary Material.
7 Other applications of machine-learning techniques to business-cycle forecasting include the research by Giusto and Piger, 2017, who use an algorithm known as Learning Vector Quantization (LVQ) to predict U.S. business-cycle turning points. Qi (2001) uses a neural network (NN) to inspect the predictive value of leading indicators for the probability of a future U.S. recession.
8 Hastie, Tibshirani and Friedman (2009, Table 10.1) summarize the pros and cons of tree-based methods relative to other popular machine-learning techniques. As compared to neural networks and support-vector machines, tree-based methods are robust to outliers in predictors, insensitive to monotone transformations of inputs, and they are able to handle irrelevant predictors. At the same time, a shortcoming of trees is their limited ability to identify linear combinations of features. Moreover, another shortcoming of trees, one that is particularly relevant in the context of our application, is that their predictive ability is less favourable then compared with neural networks and support-vector machines. An ensemble of trees remedies this shortcoming, and the BRT approach in particular is an ensemble-based model that attempts to overcome this problem "…so as to produce an accurate and effective off-the-shelf procedure for data mining." (Hastie, Tibshirani and Friedman, 2009, 352).
9 See http://www.nber.org/cycles.html.
10 The data are available at http://apps.olin.wustl.edu/faculty/manela/mm/nvix/nvix_interactive.html. Data for 1982/01–1882/06 and 1992/02 are missing. We filled these gaps in the data using linear interpolation. We summarize results for a shorter sample pieord in the Supplementary Material.
11 Data for the short rate come from the website of Amit Goyal: http://www.hec.unil.ch/agoyal/ The short-term interest rate is measured in terms of the 3-month Treasury bill rate from 1920 onwards, and prior is based on an estimation, as in Welch and Goyal (2008), using the Commercial paper rates for New York City, which are obtained from the National Bureau of Economic Research (NBER) Macrohistory database. Data on the consumer-price index, the S&P500, 10-year government bonds, the price-dividend and the price-earning data are from Robert J. Shiller's website: http://www.econ.yale.edu/ shiller/. Data on the exchange rate are from Three Centuries of Macroeconomic data maintained by the Bank of England at: http://www.bankofengland.co.uk/research/Pages/datasets/default.aspx.
12 A figure plotting the data is available from the authors upon request.
13 We summarize results for some other calibrations of the hyperparameters of the BRT approach along with results of several additional robustness checks (another metric of forecast performance, comparison with the performance of a Probit model, results when recessions are observed with a delay, results for a shorter sample period in the Supplementary Material.
14 Over the very long sample period that we study in this research, the structure and the dynamics of the U.S. economy most likely have changed several times. Evidence of structural breaks has been reported even for much shorter sample periods. For example, Chauvet and

Potter (2002), using U.S. data from January 1967 to December 2000, study the effect of structural breaks on the probability of recession estimated by means of Probit models. They find strong strong evidence of a structural break, where there is considerable uncertainty regarding the exact location of a break. See Chauvet and Potter (2005, 2010) on how variants of Probit models can account for potential sources of structural instabilities. For an example of a data-driven Probit-based approach to forecasting recessions, see Section the Supplementary Material.

15 We also considered a third specification that only features the war-related NVIX component in addition to the predictors of the baseline specification. This third specification mainly adds to the predictive performance of the BRT approach relative to the second specification that features all NVIX components in the first half of the sample period in case of 3 and 12 months-ahead forecasts. Results are not reported (but aare available from the authors upon request).

16 The test results are not reported, but available from the authors upon request.

17 Ratcliff (2013) shows for a standard Probit/Logit model that a dynamic variant of such a model that includes the lagged recession indicator corresponds to a static model without a lagged recession indicator extended to include additional lags of the predictors according to a geometric weighting scheme.

18 We summarize results that we obtain when we assume that recessions are observed with a delay in the Supplementary Material.

19 In order to inspect the robustness of our results, we also estimate a variant of the dynamic model that excludes the first and the second lag of the recession indicator from the list of predictors. Results for this variant of the dynamic model (not reported, but available from the authors upon request) are qualitatively similar to the results for the dynamic model that we describe in this section. For the implications of assuming a publication lag for the NBER recession indicator, see the Supplementary Material.

20 We use the following predictors: 17 predictors × 12 lags + 17 contemporaneous predictors + 12 lagged recession indicators.

References

Aghion, P., X. Jaravel, T. Persson, and D. Rouzet. 2014. *Education and military rivalry*. Mimeo: Harvard University. Available at https://scholar.harvard.edu/files/aghion/files/education_and_military_rivalry_0.pdf.

Alfaro, E., García M. Gámez, and D. Elizon. 2008. "Bankruptcy Forecasting: An Empirical Comparison of AdaBoost and Neural Networks." *Decision Support Systems* 45: 110–122.

Anderton, C. H., and J. H. Carter. 2001. "The Impact of War on Trade: An Interrupted Time-Series Study." *Journal of Peace Research* 38: 445–457.

Azzimonti, M. 2018. "Partisan Conflict and Private Investment." *Journal of Monetary Economics* 23: 114–131.

Bachmann, R., and C. Bayer. 2013. "'Wait-and-See' Business Cycles?" *Journal of Monetary Economics* 60: 704–719.

Bachmann, R., S. Elstner, and E. Sims. 2013. "Uncertainty and Economic Activity: Evidence from Business Survey Data." *American Economic Journal: Macroeconomics* 5: 217–249.

Bai, J., and S. Ng. 2009. "Boosting Diffusion Indices." *Journal of Applied Econometrics* 24: 607–629.

Baker, S. G., and B. S. Kramer. 2007. "Peirce, Youden, and Receiver Operation Characteristic Curves." *The American Statistician* 61: 343–346.

Baker, S., N. Bloom, and S. Davis. 2016. "Measuring Economic Policy Uncertainty." *Quarterly Journal of Economics* 131: 1593–1636

Balcilar, M., R. Gupta, and M. Segnon. 2016. "The Role of Economic Policy Uncertainty in Predicting U.S. Recessions: A Mixed-Frequency Markov-Switching Vector Autoregressive Approach." *Economics: The Open-Access, Open-Assessment E-Journal* 10 (2016–27): 1–20.

Balcilar, M., R. Demirer, R. Gupta, and R. van Eyden. 2017a. "The Impact of US Policy Uncertainty on the Monetary Effectiveness in the Euro Area." *Journal of Policy Modeling* 39: 1052–1064.

Balcilar, M., R. Gupta, and C. Jooste. 2017b. "Long Memory, Economic Policy Uncertainty, and Forecasting US Inflation: A Bayesian VARFIMA Approach." *Applied Economics* 49: 1047–1054.

Bali, T. G., S. J. Brown, and Y. Tang. 2015. "Macroeconomic Uncertainty and Expected Stock Returns." Georgetown McDonough School of Business, Research Paper No. 2407279.

Bamber, J. D. 1975. "The Area above the Ordinal Dominance Graph and the Area Below the Receiver Operating Characteristic Graph." *Journal of Mathematical Psychology* 12: 387–425.

Barboza, F., H. Kimura, and E. Altman. 2017. "Machine Learning Models and Bankruptcy Prediction." *Expert Systems with Applications* 83: 405–417.

Barro, R. J., and J. F. Ursuá. 2017. "Stock-Market Crash and Depressions." *Research in Economics* 71: 384–398.

Behrens, C., C. Pierdzioch, and M. Risse. 2018. "A Test of the Joint Efficiency of Macroeconomic Forecasts Using Multivariate Random Forests." *Journal of Forecasting* 37: 560–572.

Berge, T. J. 2015. "Predicting Recessions with Leading Indicators: Model Averaging and Selection Over the Business Cycle." *Journal of Forecasting* 34: 455–471.

Berge, T. J., and Ò. Jordà. 2011. "Evaluating the Classification of Economic activity into Recessions and Expansions." *American Economic Journal: Macroeconomics* 3: 246–277.

Bernanke, B. S. 1983. "Irreversibility, Uncertainty, and Cyclical Investment." *Quarterly Journal of Economics* 98: 85–106.

Blomberg, S. B., and G. D. Hess. 2006. "How much does Violence Tax Trade?" *Review of Economics and Statistics* 88: 599–612.

Bloom, N. 2009. "The Impact of Uncertainty Shocks." *Econometrica* 77: 623–685.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry. 2014. *Really Uncertain Business Cycles*. Mimeo: Stanford University.

Bluedorn, J. C., J. Decressin, and M. E. Terrones. 2016. "Do Asset Price Drops Foreshadow Recessions?" *International Journal of Forecasting* 32: 518–526.

Born, B., and J. Pfeifer. 2014. "Policy Risk and the Business Cycle." *Journal of Monetary Economics* 68: 68–85.

Breiman, L., J. H. Friedman, R. A. Olshen, and C. J. Ston. 1984. *Classification and Regression Trees*. Monterey: Wadsworth and Brooks/Cole.

Brogaard, J., and A. Detzel. 2015. "The Asset-Pricing Implications of Government Economic Policy Uncertainty." *Management Science* 61: 3–18.

Buchen, T., and K. Wohlrabe. 2011. "Forecasting with Many Predictors: Is Boosting a Viable Alternative?" *Economics Letters* 113: 16–18.

Caggiano, G., E. Castelnuovo, and N. Groshenny. 2014. "Uncertainty Shocks and Unemployment Dynamics in US Recessions." *Journal of Monetary Economics* 67: 78–92.

Caggiano, G., E. Castelnuovo, and J. M. Figueres. 2017a. "Economic Policy Uncertainty and Unemployment in the United States: A Nonlinear Approach." *Economics Letters* 151: 31–34.
Caggiano, G., E. Castelnuovo, and G. Pellegrino. 2017b. "Estimating the Real Effects of Uncertainty Shocks at the Zero Lower Bound." *European Economic Review* 100: 257–272.
Caldara, D., and M. Iacoviello. 2016. "Measuring Geopolitical Risk." Working Paper, Board of Governors of the Federal Reserve Board.
Caldara, D., C. Fuentes-Albero, S. Gilchrist, and E. Zakrajšek. 2016. "The macroeconomic impact of financial and uncertainty shocks." *European Economic Review* 88(C): 185–207.
Carriero, A., H. Mumtaz, A. Theophilopoulou, and K. Theodoridis. 2015. "The Impact of Uncertainty Shocks Under Measurement Error: A Proxy SVAR Approach." *Journal of Money, Credit and Banking* 47: 1223–1238.
Chauvet, M., and S. Potter. 2002. "Predicting a Recession: Evidence from the Yield Curve in the Presence of Structural Breaks." *Economics Letters* 77: 245–253.
Chauvet, M., and S. Potter. 2005. "Forecasting Recessions Using the Yield Curve." *Journal of Forecasting* 24: 77–103.
Chauvet, M., and S. Potter. 2010. "Business Cycle Monitoring with Structural Changes." *International Journal of Forecasting* 26: 777–793.
Christiano, L., R. Motto, and M. Rostagno. 2014. "Risk Shocks." *American Economic Review* 104: 27–65.
Christidou, M., and S. Fountas. 2018. "Uncertainty in the Housing Market: Evidence from US States." *Studies in Nonlinear Dynamics and Econometrics* 22: 20160064.
Chuliá, H., M. Guillén, and J. M. Uribe. 2017. "Measuring Uncertainty in the Stock Market." *International Review of Economics and Finance* 48: 18–33.
Creal, D. D., and C. Wu. 2017. "Monetary Policy Uncertainty and Economic Fluctuations." *International Economic Review* 58: 1317–1354.
Diaz, D., B. Theodoulidis, and C. Dupouy. 2016. "Modelling and Forecasting Interest Rates During Stages of the Economic Cycle: A Knowledge-Discovery Approach." *Expert Systems with Applications* 44: 245–264.
Dixit, A. K., and R. S. Pindyck. 1994. "*Investment Under Uncertainty*. Princeton, New Jersey: Princeton University Press.
Döpke, J., U. Fritsche, and C. Pierdzioch. 2017. "Predicting Recessions with Boosted Regression Trees." *International Journal of Forecasting* 33: 745–759.
Dueker M. 1997. "Strengthening the Case for the Yield Curve as a Predictor of U.S. Recessions." *Federal Reserve Bank of St. Louis Review* 79: 41–51.
Estrella, A., and F. S. Mishkin. 1998. "Predicting US Recessions: Financial Variables as Leading Indicators." *Review of Economics and Statistics* 80: 45–61.
Estrella, A., A. P. Rodriguez, and S. Schich. 2003. "How Stable is the Predictive Power of the Yield Curve? Evidence from Germany and the United States." *Review of Economics and Statistics* 85: 629–644.
Fernández-Villaverde, J., P. Guerrón-Quintana, J. F. Rubio-Ramírez, and M. Uribe. 2011. "Risk Matters: The Real Effects of Volatility Shocks." *American Economic Review* 101: 2530–2561.
Fernández-Villaverde, J., P. Guerrón-Quintana, K. Kuester, and J. F. Rubio-Ramírez. 2015. "Fiscal Volatility Shocks and Economic Activity." *American Economic Review* 105: 3352–3384.
Foerster, A. 2014. "The Asymmetric Effects of Uncertainty on Employment. Federal Reserve Bank of Kansas City." *Economic Review Quarter* 3: 5–26.
Freund, Y., and R. E. Schapire. 1997. "A Decision-Theoretic Generalization of on-Line Learning and an Application to Boosting." *Journal of Computer and System Sciences* 55: 119–139.
Friedman, J. H. 2001. "Greedy Function Approximation: A Gradient Boosting Machine." *The Annals of Statistics* 29: 1189–1232.
Friedman, J. H. 2002. "Stochastic Gradient Boosting." *Computational Statistics and Data Analysis* 38: 367–378.
Friedman, J. H., T. Hastie, and R. Tibshirani. 2000. "Additive Logistic Regression: A Statistical View of Boosting." *The Annals of Statistics* 28: 337–407.
Giusto, A., and J. Piger. 2017. "Identifying Business Cycle Turning Points in Real Time with Vector Quantization." *International Journal of Forecasting* 33: 174–184.
Gourio, F. 2012. "Disaster Risk and Business Cycles." *American Economic Review* 102: 2734–2766.
Greiner, M., D. Pfeiffer, and R. D. Smith. 2000. "Principles and Practical Application of the Receiver-Operating Characteristic Analysis for Diagnostic Tests." *Preventive Veterinary Medicine* 45: 23–41.
Gupta, R., and C. Jooste. 2018. "Unconventional Monetary Policy Shocks in OECD Countries: How Important is the Extent of Policy Uncertainty?" *International Economics and Economic Policy* 15: 683–703.
Gupta, R., C.-K.-M. Lau, and M. E. Wohar. 2019. "The Impact of US Uncertainty on the Euro Area in Good and Bad Times: Evidence from a Quantile Structural Vector Autoregressive Model." *Empirica* 46:353–365. DOI: 10.1007/s10663-018-9400-3.
Gupta, R., J. Ma, M. Risse, and M. E. Wohar. 2018. "Common Business Cycles and Volatilities in US States and MSAs: The Role of Economic Uncertainty." *Journal of Macroeconomics* 57: 317–337.
Hanley, J. A., and B. J. McNeil. 1982. "The Meaning and Use of the Area Under a Receiver Operating Characteristic Curve." *Radiology* 143: 29–36.
Hastie, T., R. Tibshirani, and J. Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* Berlin: Springer.
Hsu, M. W., S. Lessmann, M.-C. Sung, T. Ma, and J. E. V. Johnson. 2016. "Bridging the Divide in Financial Market Forecasting: Machine Learners vs. Financial Economists." *Expert Systems with Applications* 61: 215–234.
Jones, P. M., and E. Olson. 2013. "The Time-Varying Correlation between Uncertainty, Output and Inflation: Evidence from a DCC-GARCH model." *Economics Letters* 118: 33–37.
Jones, P. M., and W. Enders. 2016. "The Asymmetric Effects of Uncertainty on Macroeconomic Activity." *Macroeconomic Dynamics* 20: 1219–1246.
Jones, P. M., and E. Olson. 2015. "The International Effects of US Uncertainty." *International Journal of Finance and Economics* 20: 242–252.
Junttila, J.-P., and J. Vataja. 2017. "A Random Walk Down the Economic Policy Street: Effects of Economic Policy Uncertainty on Forecasting Future Real Economic Activity in the Euro Area and the UK." Working Paper, Available at SSRN: https://ssrn.com/abstract=2919400.

Jurado, K., S. Ludvigson, C., and S. Ng. 2015. "Measuring Uncertainty." *American Economic Review* 105: 1177–1216.
Kang, W., K. Lee, and R. A. Ratti. 2014. "Economic Policy Uncertainty and Firm-Level Investment." *Journal of Macroeconomics* 39: 42–53.
Karnizova, L., and J. C. Li. 2014. "Economic Policy Uncertainty, Financial Markets and Probability of US Recessions." *Economics Letters* 125: 261–265.
Kauppi, H., and P. Saikkonen. 2008. "Predicting U.S. Recessions with Dynamic Binary Response Models." *Review of Economics and Statistics* 90: 777–791.
Kostka, T., and B. van Roye. 2017. "Assessing the Decoupling of Economic Policy Uncertainty and Financial Conditions." *Financial Stability Review, European Central Bank* May: 1–9.
Larsen, V. H. 2017. "Components of Uncertainty." Norges Bank, Working Paper No. 05/2017.
Lehmann, R., and K. Wohlrabe. 2016. "Looking into the Black Box of Boosting: The Case of Germany." *Applied Economics Letters* 23: 1229–1233.
Lensink, B. W., and V. Murinde. 2006. "The Inverted-U Hypothesis for the Effect of Uncertainty on Investment: Evidence from UK Firms." *European Journal of Finance* 12: 95–105.
Lin, K.-P., and P.-F. Pai. 2010. "A Fuzzy Support Vector Regression Model for Business Cycle Predictions." *Expert Systems with Applications* 37: 5430–5435.
Liu, W., and E. Moench. 2016. "What Predicts U.S. Recessions?" *International Journal of Forecasting* 32: 1138–1150.
Ludvigson, S. C., S. Ma, and S. Ng. 2015. "Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?" National Bureau of Economic Research, Working Paper No. w21803, Cambridge, Mass.
Ma, J., E. Olson, and M. E. Wohar. 2018. "Nonlinear Taylor Rules: Evidence from a Large Dataset." *Studies in Nonlinear Dynamics and Econometrics* 22: 20160082.
Manela, A. and A. Moreira. 2017. "News Implied Volatility and Disaster Concerns." *Journal of Financial Economics* 123: 137–162.
Manasse, P., and N. Roubini. 2009. "'Rules of Thumb' for Sovereign Debt Crises." *Journal of Internatwional Economics* 78: 192–205.
Mumtaz, H., and F. Zanetti. 2013. "The Impact of the Volatility of Monetary Policy Shocks." *Journal of Money, Credit and Banking* 45: 535–558.
Mumtaz, H., and K. Theodoridis. 2017. "Common and Country Specific Economic Uncertainty." *Journal of International Economics* 105: 205–216.
Mumtaz, H., and P. Surico. 2018. "Policy Uncertainty and Aggregate Fluctuations." *Journal of Applied Economerics* 33: 319–331.
Mumtaz, H., and K. Theodoridis. 2018. "The Changing Transmission of Uncertainty Shocks in the US: An Empirical Analysis." *Journal of Business and Economic Statistics* 36: 239–252.
Mumtaz, H., L. Sunder-Plassmann, and A. Theophilopoulou. 2018. "The State Level Impact of Uncertainty Shocks." *Journal of Money, Credit, and Banking* 50: 1879–1899.
Ng, S. 2014. "Boosting Recessions." *Canadian Journal of Economics* 47: 1–34.
Nodari, G. 2014. "Financial Regulation Policy Uncertainty and Credit Spreads in the US." *Journal of Macroeconomics* 41: 122–132.
Nyberg, H. 2010. "Dynamic Probit Models and Financial Variables in Recession Forecasting." *Journal of Forecasting* 29: 215–230.
Oztekin, A., R. Kizilaslan, S. Freund, and A. Iseri. 2016. "A Data Analytic Approach to Forecasting Daily Stock Returns in an Emerging Market." *European Journal of Operational Research* 253: 697–710.
Pellegrino, G. 2014. "Uncertainty and Monetary Policy in the US: A Journey into Non-Linear Territory." University of Padoa, Dipartimento di Scienze Economiche, 'Marco Fanno' Working Paper No. 0184.
Pellegrino, G. 2018. "Uncertainty and the Real Effects of Monetary Policy Shocks in the Euro Area." *Economics Letters* 162: 177–181.
Pierdzioch, C., M. Reid, and R. Gupta. 2018. "On the Directional Accuracy of Inflation Forecasts: Evidence from South African Survey Data." *Journal of Applied Statistics* 45: 884–900.
Qi, M. 2001. "Predicting US Recessions with Leading Indicators via Neural Network Models." *International Journal of Forecasting* 17: 383–401.
R Core Team. 2015. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. URL http://www.R-project.org/.
Ratcliff, R. 2013. "The 'Probability of Recession': Evaluating Probabilistic and Non-Probabilistic Forecasts from Probit Models of U.S. Recessions." *Economics Letters* 121: 311–315.
Ridgeway, R. W. C. F. O. 2015. *gbm: Generalized Boosted Regression Models*. R package version 2.1.1. http://CRAN.R-project.org/package=gbm.
Robinzonov, N., G. Tutz, and T. Hothorn. 2012. "Boosting Techniques for Nonlinear Time Series Models." *AStA Advances in Statistical Analysis* 96: 99–122.
Rossi, B., and T. Sekhposyan. 2015. "Macroeconomic Uncertainty Indices Based on Nowcast and Forecast Error Distributions." *American Economic Review Papers and Proceedings* 105: 650–655.
Rossi, B., T. Sekhposyan, and M. Soupre. 2016. *Understanding the Sources of Macroeconomic Uncertainty*. Mimeo: Universitat Pompeu Fabra–Centre de Recerca en Economia Internacional (CREI).
Rudebusch, G. D., and J. C. Williams. 2009. "Forecasting Recessions: The Puzzle of the Enduring Power of the Yield Curve." *Journal of Business and Economics Statistics* 27: 492–503.
Sarkar, S. 2000. "On the Investment-Uncertainty Relationship in a Real Options Model." *Journal of Economic Dynamics and Control* 24: 219–225.
Scotti, C. 2016. "Surprise and Uncertainty Indexes: Real-Time Aggregation of Real-Activity Macro Surprises." *Journal of Monetary Economics* 82: 1–19.
Segnon, M., R. Gupta, S. Bekiros, and M. E. Wohar. 2018. "Forecasting US GNP Growth: The Role of Uncertainty." *Journal of Forecasting* 37: 541–559.
Shin, M., and M. Zhong. 2016. *A New Approach to Identifying the Real Effects of Uncertainty Shocks.* Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series 2016–040.
Welch, I., and A. Goyal. 2008. "A Comprehensive Look at the Empirical Performance of Equity Premium Prediction." *Review of Financial Studies* 21: 1455–1508.
Wohlrabe, K, and T. Buchen. 2014. "Assessing the Macroeconomic Forecasting Performance of Boosting: Evidence for the United States, the Euro Area and Germany." *Journal of Forecasting* 33: 231–242.

Supplementary Material: The online version of this article offers supplementary material (DOI: https://doi.org/10.1515/snde-2018-0083).