Nowcasting Recession Risk[*][†]

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Abstract

We propose a simple yet robust framework to nowcast recession risk at a monthly frequency in both the United States and the Euro Area. Our nowcast leverages both macroeconomic and financial conditions, and is available the first business day after the reference month closes. In particular, we argue that financial conditions are not only useful to predict future downturns–as emphasized by the existing literature–but they are also useful to distinguish between expansions and downturns as they unfold. We then connect our recession risk nowcast with growth-at-risk by drawing on the literature on distributional regressions and quantile regressions. Finally, we benchmark our nowcast with the Survey of Professional Forecasters (SPF) and show that, while both have a similar ability to identify downturns, the former is more accurate in correctly identifying periods of expansion.

Keywords: Recessions, Nowcasting, Risk, Growth-at-Risk, Financial Conditions, Distributional Regression

1 Introduction

"Is the economy currently experiencing a recession?" is the question we attempt to answer in this chapter. To do so, we build a simple yet robust Bayesian logit framework to nowcast recession risk at a monthly frequency in both the United States and the Euro Area. Our nowcast leverages one macroeconomic and one financial predictor, and is available the first business day after the reference month closes. For example, the estimate of recession risk for–say–October is available the first business day of November. Thanks to our careful selection of predictors, it is also subject to minimal revisions.

The recurrence of recessions after periods of expansions is one of the most robust features of the business cycle over the centuries - see Mitchell (1913) and Mitchell (1927). As famously summarized by Burns and Mitchell (1946): *"Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises. A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary"*.

Despite the simplicity of the notion of recession, timely knowledge of whether the economy is experiencing a broad-based decline in economic activity is a key input to a variety of decision-making processes. For example, firms may pause an investment project in anticipation of an imminent recession, or may resume a hiring plan were they to learn that a recovery is under way. A central bank fighting inflation may decide to halt a monetary tightening cycle upon receiving signals of an ongoing recession. High demand for this type of information is what has motivated, for example, the addition of a question on recession risk in both the *Survey of Market Participants (SMP)* and the *Survey of Primary Dealers (SPD)* of the Federal Reserve Bank of New York.

Surprisingly, the tools available to assess recession risk in real time are limited. On the one hand, business cycle dating committees officially announce recessions with a delay of months, if not years. On the other hand, national economic accounts are subject to revisions and are also released with a sizable delay. For example, most of the data series monitored by the NBER dating committee are released one to two months after the month of reference concludes. Survey-based measures of recession risk are infrequent and released with a delay, and model-based estimates–such as Chauvet and Piger (2008)–are available with a delay of more than one month because of publication lags in the underlying data.

This chapter's goal is to expand the toolkit available to economists to monitor recession risk in real-time. We build our nowcasting framework by leveraging a Bayesian logit to project official recession dates for the US and the Euro Area on a macroeconomic predictor–the PMI Manufacturing for the US and the Economic Sentiment Indicator (ESI) for the Euro Area–and a financial predictor–the Composite Index of Systemic Stress (CISS) for both areas. We argue that financial conditions are not only useful to predict future downturns, as emphasized by the existing literature, but they are also useful to nowcast the state of the economy and to distinguish between expansions and downturns as they unfold. In particular, we argue that financial conditions, when added to macroeconomic indicators, increase the ability to identify downturns.

We then connect our recession risk nowcast with growth-at-risk by drawing on the literature on distributional regressions and quantile regressions. Finally, we benchmark our nowcast with the Survey of Professional Forecasters (SPF) and show that, while both have a similar ability to identify downturns, the former is more accurate in correctly identifying periods of expansion. All these properties make our nowcasting framework an additional tool to support business cycle dating committees in both the US and the Euro Area.

We connect our results to several strands of research. One is concerned with nowcasting economic activity–see Giannone, Reichlin and Small (2008), Bańbura, Giannone, Modugno and Reichlin (2013), Bok, Caratelli, Giannone, Sbordone and Tambalotti (2018), and the chapter by Cascaldi-Garcia, Luciani and Modugno in this volume. This literature has focused on the prediction of the central tendency of the growth rate of GDP. Here, instead, we estimate the risk of a significant and broad decline in economic activity.

The second strand of literature focuses on future recessions and estimates the probability of a recession over a certain forecasting horizon. The main finding of this literature is that yield-curve spreads tend to be the most accurate predictors of future recessions–see among others Stock and Watson (1989), Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Chauvet and Potter (2005), Wright (2006), Kauppi and Saikkonen (2008). Here, we focus on estimating the risk of *currently* being in a recession, instead of trying to predict a future one.

The third strand of literature focuses on estimating the distribution of real GDP growth and quantifying downside risk to economic activity. Since recessions tend to coincide with two quarters of negative growth, we show in section 4 that our recession risk nowcast can be seen as an estimator of the conditional cumulative distribution of GDP growth evaluated at 0. This has two consequences. First, one could resort to a wide set of existing statistical tools from the distributional regression literature to nowcast recession risk. Second, recession risk and growth-at-risk are tightly connected because the conditional CDF of GDP growth coincides, most of the time, with a low quantile in the growth-at-risk framework–also see Peracchi (2002), Koenker, Leorato and Peracchi (2013), Chernozhukov, Fernández-Val and Melly (2013) on the connection between quantile and distributional regressions. Therefore, recession risk is another way to think about the growth-at-risk framework proposed by Adrian, Boyarchenko and Giannone (2019), and further developed in a fast-growing literature which includes, among others, Adams, Adrian, Boyarchenko and Giannone (2021), Adrian, Grinberg, Liang, Malik and Yu (2022), and Chernis, Coe and Vahey (2023). This important connection has also been pointed out by Boyarchenko, Giannone and Kovner (2020).

2 Methodology

This section describes our recession dating approach, choice of predictors, and econometric framework to nowcast recession risk. We align with the NBER (National Bureau of Economic Research) and CEPR-EABCN (Centre for Economic Policy Research-Euro Area Business Cycle Network) official business cycle dating approach to identify periods of recessions, and we nowcast recession risk by projecting monthly recession dummies against monthly macroeconomic and financial predictors using a Bayesian logit specification.

2.1 Recession Dates

Official business cycle dates reflect a robust and broad-based contraction in economic activity, and we adopt them to identify periods of expansion and periods of contractions. Indeed, according to the NBER business cycle dating committee, recessions entail *"a significant decline in economic activity that is spread across the economy and lasts more than a few months"*. Table 1 and Table 2 report official recession dates, together with their announcement date. Since recessions in the Euro Area are identified at a quarterly frequency by the Euro Area Business Cycle Dating Committee, we assume that each month in a recession quarter is a recession month. This assumption allows us to construct recession dates at a monthly frequency for the Euro Area as well.

Table 1: United States Official Recessions Dates

Start	Announced	End	Announced
January 1980	June 1980	July 1980	July 1981
July 1981	January 1982	November 1982	July 1983
July 1990	April 1991	March 1991	December 1992
March 2001	November 2001	November 2001	July 2003
December 2007	December 2008	June 2009	September 2010
February 2020	June 2020	April 2020	July 2021

Table 2: Euro Area Official Recessions Dates

Start	Announced	End	Announced
1974q3	September 2003	1975q1	September 2003
1980q1	September 2003	1982q3	September 2003
1992q1	September 2003	1993q3	September 2003
2008q1	March 2009	2009q2	October 2010
2011q3	November 2012	2013q1	October 2015
2019q4	September 2020	2020q2	November 2021

Separating periods of economic expansion from periods of contraction presents important challenges, due to both the heterogeneous behavior of different segments of the economy and to the noisy nature of macroeconomic data - see Crump, Giannone and Lucca (2020a) and Crump, Giannone and Lucca (2020b) for an overview of these issues. As a result, official business cycle dates are announced with a significant delay to allow dating committees to collect all the necessary data and consider the impact of data revisions.

This announcement delay results in a well-known econometric issue when predicting recessions, since the dependent variable Y_t is available with a variable lag. A common solution in the literature is to estimate, at a generic time t, the coefficients of the model using information up to $t - d$, where d is a fixed estimation delay - see Kauppi and Saikkonen (2008), Nyberg (2010), Ng (2012). In line with previous studies, we set $d = 24$ (i.e., two years) when performing out-of-sample estimation, even though our results are robust to smaller or larger values of d.

It is also possible to replace official recession dates with unofficial recession dates constructed using an algorithmic procedure or a model-based one–see for example Bry and Boschan (1971), Hamilton (1989), Stock and Watson (1989), Harding and Pagan (2002), Harding and Pagan (2006), Chauvet and Piger (2008), Berge and Jordà (2011), Hamilton (2011), Stock and Watson (2014). In section 4, since recessions almost perfectly coincide with two quarters of negative growth–an insight that can be formalized by the Bry-Boschan quarterly (BBQ) algorithm proposed by Harding and Pagan (2002)–we proxy recessions with the contraction in real GDP over two quarters to highlight the connection between our recession risk nowcast and the conditional distribution of real GDP growth.

2.2 Macroeconomic and Financial Predictors

One of the main contributions of this chapter is to highlight the importance of financial conditions to understand whether the economy is currently experiencing a recession, and Figure 1 clarifies why. The figure reports concurrent macroeconomic and financial conditions across periods of expansion (orange) and recession (blue) for both the United States and the Euro Area. Periods of expansions are characterized by good readings of both macroeconomic indicators and financial conditions (top-left corner), while the opposite is true during recessions (bottom-right corner). Importantly, the overlap between the two conditional distributions of the predictors is minimal, which suggests that examining financial conditions on top of standard macroeconomic indicators should improve our ability to detect recessions in real-time.
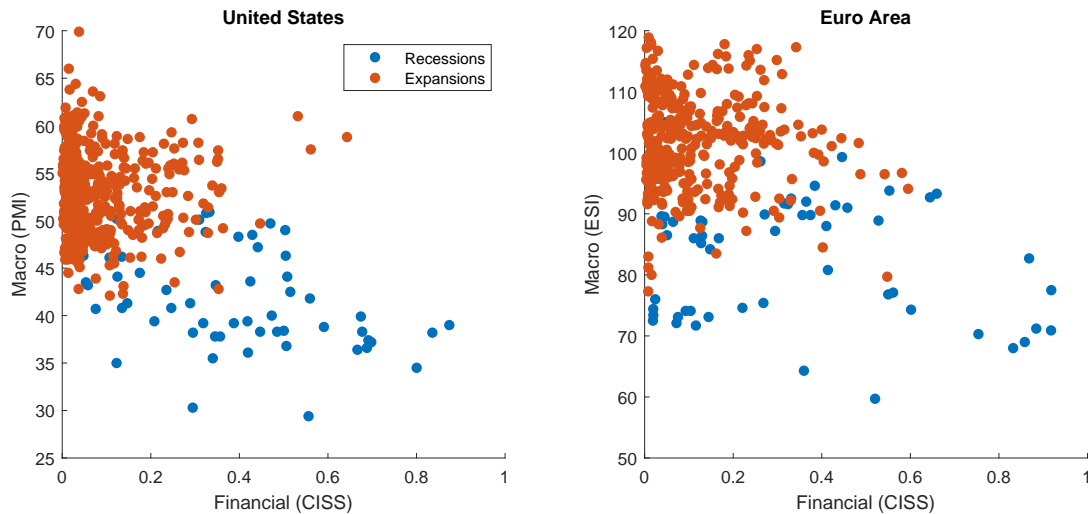

Figure 1: Macroeconomic and Financial Conditions during Recessions and Expansions
Note: Each dot represents macroeconomic and financial conditions in a different month.

The choice to prioritize the inclusion of financial conditions is also motivated by the insight in Adrian et al.

(2019) that financial conditions are particularly informative about downside risk to GDP growth - which in section 4 we connect to recession risk. While financial conditions are usually leveraged to predict future recessions, we argue that they are an even more powerful tool to understand the coincident state of the economy.

Our choice of predictors is summarized in Table 3. For each geographical area, we select one indicator of macroeconomic activity and one indicator of financial conditions. To perform an effective real-time now-casting exercise, each predictor should be available at a monthly frequency, timely, and subject to minimal revisions. These requirements led us to select the ISM Purchasing Managers' Index (PMI) Manufacturing for the US, the European Commission's Economic Sentiment Indicator (ESI), and the ECB's Composite Indicator of Systemic Stress (CISS) for both areas.

Table 3: Macroeconomic and Financial Predictors

Area	Indicator	Source	Frequency	Series Start	Release Timing
US	Composite Indicator of Systemic Stress	ECB	D	1980m1	Current Month
US	PMI Manufacturing	ISM	M	1948m1	Beginning Next Month
EA	Composite Indicator of Systemic Stress	ECB	D	1980m1	Current Month
EA	Economic Sentiment Index	EC	M	1985m1	End of Current Month

Note: "ECB" stands for European Central Bank, "ISM" stands for Institute for Supply Management, "EC" stands for European Commission, "D" stands for daily, "M" stands for monthly. The PMI Manufacturing for a given month is released on the first business day of the following month.

The Economic Sentiment Indicator (ESI) and the PMI Manufacturing are both monthly surveys that ask qualitative questions on the state of the economy which are then aggregated into a diffusion index. The ESI covers industry (weight 40%), services (30%), consumers (20%), retail (5%) and construction (5%), while the Manufacturing PMI focuses on manufacturing firms. Despite the rising importance of the service sector for business cycle dynamics, the Manufacturing PMI remains highly informative and has the additional advantage of being available over a longer time period - see Lahiri and Monokroussos (2013). For the Euro Area, we chose the ESI over the PMI because of its longer availability, but the two measures capture very similar signals (although the ESI focuses more on sentiment as opposed to actual conditions). "Soft" business surveys such as the PMI are widely followed by financial market participants and business economists because they provide a timely and accurate signal of the state of the economy.

To measure financial conditions, we resort to the Composite Indicator of Systemic Stress (CISS), which was originally developed by Hollo, Kremer and Lo Duca (2012) and is now maintained by the ECB - see Chavleishvili and Kremer (2023). The CISS measures financial stress using financial prices across five different market segments (bonds, equities, money markets, foreign exchange markets, financial intermediaries), and then aggregates them using a portfolio-theoretic approach that accounts for the cross-segment correlation. The index is produced at a daily frequency and is available since January 1980 for several geographical areas, including the US and the Euro Area.[1] The CISS has been used to model the conditional distribution of GDP growth in Figueres and Jarociński (2020), Adams, Adrian, Boyarchenko, Giannone, Liang and Qian (2020), and Adrian, Boyarchenko and Giannone (2021), and it comoves strongly with the popular Chicago's

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[1]An important caveat is that the CISS has been introduced in 2012 and backdated to 1980.

National Financial Conditional Index (NFCI) used in Adrian et al. (2019). The latter, however, is subject to revisions and is only available for the US. We construct monthly values of the CISS series by averaging daily values.

Figure 2 below provides a visualization of our predictors during the sample period, which covers our sample period from 1980:m1 to 2021:m12.
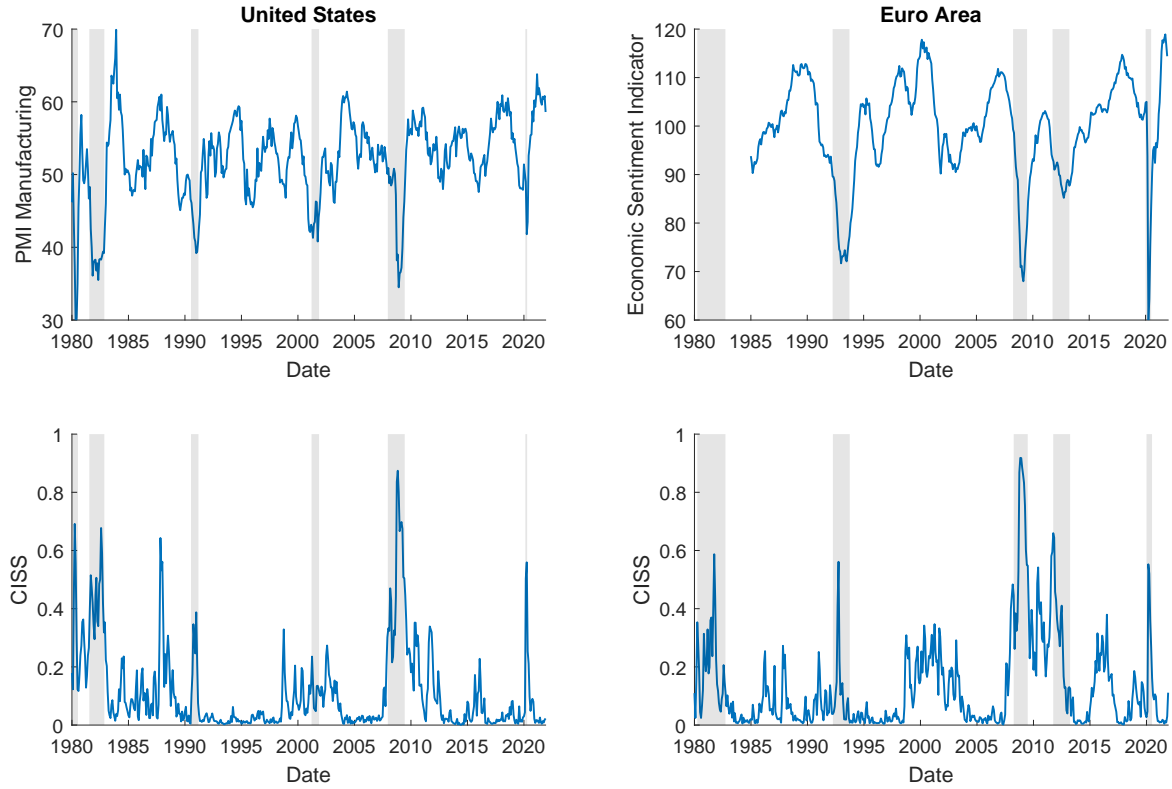

Figure 2: Economic and Financial Predictors
Note: Shaded bars correspond to official NBER and CEPR recessions.

Importantly, all our predictors are timely: they are available immediately after the month of reference closes and thus permit to estimate recession risk with a minimal delay. Furthermore, they are subject to minimal revisions. The CISS is constructed to be a real-time indicator: this is achieved thanks to the use of financial market prices (not revised) in conjunction with a recursive statistical procedure to normalize its values. The responses to the ISM PMI Manufacturing are never revised, and the only revision is generated by the seasonal factors which are updated annually. Unfortunately, we do not have access to the PMI Manufacturing data vintages, but the revisions tend to be minimal and do not impact our estimates of recession risk. Finally, the ESI is subject to minor revisions in the underlying data and to an annual re-standardization procedure. In practice, these revisions do not affect our estimates, as we show in Figure 5 in the Appendix.

2.3 Econometric Specification and Estimation

We estimate recession risk using a logit model estimated using Bayesian methods. While we prefer a Bayesian logit specification, our results are robust to the econometric specification and the estimation

method adopted. In section 4, we highlight the connection between our approach and the conditional distribution of real GDP growth estimated using distributional regressions. More formally, let $Y^T_{T\times 1} = [Y_1, ..., Y_T]'$ be the sample of recession observations where

$$Y_t = \begin{cases} 1 & \text{if economy in recession in month } t \\ 0 & \text{otherwise} \end{cases}$$

and let $X^T_{T\times K} = [X'_1, ..., X'_T]'$ be a sample of K predictors. We assume that

$$Y_t | \pi_t \sim_{iid} Bern(\pi_t) \tag{1}$$

where π_t is the probability of a recession happening in month t, and is our object of interest. We assume that recession risk depends on the set of predictors through a logit-link function, that is

$$\pi_t = F(X_t \cdot \beta) = \frac{\exp(X_t \cdot \beta)}{1 + \exp(X_t \cdot \beta)} \tag{2}$$

where $F(\cdot)$ is the cumulative density function of a logistic distribution. This is the same econometric approach found in the literature on predicting future recessions using the term-structure of interest rates, where $F(\cdot)$ is often assumed to be the cumulative density function of a standard normal distribution. An implicit assumption behind our modeling choice is that the set of predictors X_t at time t is sufficient to summarize recession risk at time t. Furthermore, our model specification is sometimes referred to as a "static" logit model, as opposed to a "dynamic" logit model where lagged values of the dependent variable are introduced as predictors - see Kauppi and Saikkonen (2008) and Ng (2012) for a discussion. Together, Equation 1 and Equation 2 imply that

$$Y_t | X_t, \beta \sim_{iid} Bern\left(\frac{\exp(X_t \cdot \beta)}{1 + \exp(X_t \cdot \beta)} \right). \tag{3}$$

We resort to Bayesian methods for estimation, which conveniently incorporate parameter uncertainty into our nowcast. In particular, we are interested in the posterior distribution for the $K + 1$ coefficients β, which include an intercept. As customary with Bayesian logit estimation, we set flat priors on the coefficients β by assuming normality and independence:

$$\beta_k \sim_{iid} \mathcal{N}(\mu_k, \sigma_k^2)$$

and by setting $\mu_k = 0$ and $\sigma_k^2 = 10$, for every k. As a result, the joint density of our prior is given by

$$p(\beta) = \prod_{k=1}^{K} \frac{1}{\sqrt{2\pi\sigma_k^2}} \times \exp\left(-\frac{1}{2}\left(\frac{\beta_k - \mu_k}{\sigma_k}\right)^2 \right).$$

The likelihood function is given by

$$\mathcal{L}(\beta | Y^T, X^T) = \prod_{t=1}^{T} \left(\frac{\exp(X_t \cdot \beta)}{1 + \exp(X_t \cdot \beta)} \right)^{Y_t} \times \left(1 - \frac{\exp(X_t \cdot \beta)}{1 + \exp(X_t \cdot \beta)} \right)^{1-Y_t}$$

and the posterior kernel is given by:

$$\prod_{k=1}^{K} \frac{1}{\sqrt{2\pi\sigma_k^2}} \times \exp\left(-\frac{1}{2}\left(\frac{\beta_k - \mu_k}{\sigma_k}\right)^2\right) \times \prod_{t=1}^{T} \left(\frac{\exp(X_t \cdot \beta)}{1 + \exp(X_t \cdot \beta)}\right)^{Y_t} \times \left(1 - \frac{\exp(X_t \cdot \beta)}{1 + \exp(X_t \cdot \beta)}\right)^{1-Y_t}.$$

To simulate the posterior of β, we resort to the slice sampling algorithm described in Neal (2003) and conveniently built into MATLAB. Then, to obtain the posterior density of π_t, we evaluate Equation 2 for each draw j from the posterior of β:

$$\pi_t^{(j)} = \frac{\exp(X_t \cdot \beta^{(j)})}{1 + \exp(X_t \cdot \beta^{(j)})}.$$

Finally, we take the posterior median as our point estimate and report 90% credible intervals throughout the chapter.

2.4 Accuracy Assessment

Our preferred accuracy measure for our probabilistic nowcast is the Brier Score, originally proposed by Brier (1950) to verify probabilistic weather forecasts. For a univariate probabilistic prediction, as in our application, the Brier Score coincides with the Mean Squared Error (MSE) and is given by:

$$BS = \frac{1}{T} \sum_{t=1}^{T} (\pi_t - Y_t)^2 \tag{4}$$

where T is the sample size, π_t is our nowcast of recession risk, and Y_t is the recession event. Since our Bayesian approach yields a posterior distribution for π_t, we compute the Brier Score using the posterior median. A convenient property of the Brier Score is that it can be decomposed as the sum of two terms:

$$BS = \underbrace{\frac{1}{T} \sum_{m=1}^{M} n_m (\pi_m - \bar{Y}_m)^2}_{\equiv \text{Calibration}} + \underbrace{\frac{1}{T} \sum_{m=1}^{M} n_m (\bar{Y}_m (1 - \bar{Y}_m))}_{\equiv \text{Refinement}} \tag{5}$$

where $\pi_1, ..., \pi_m, ..., \pi_M$ are the unique values of π_t, n_m is the number of times π_t takes value equal to π_m, and $\bar{Y}_m$ is the average value of the recession dummy when π_t takes value π_m. While the calibration term provides an assessment of how well the nowcast matches the unconditional frequency of observed recessions, the refinement term summarizes the ability of the nowcast to separate recessions from expansions, which requires a higher value of π_t during a recession and a lower one during an expansion.

Another convenient way to decompose the Brier Score is by separating periods of expansion from periods of recession in the following way:

$$BS = \omega_R \times BS_{|R} + \omega_E \times BS_{|E} \tag{6}$$

where ω_R represents the fraction of periods in recession, ω_E the fraction of periods in expansion, $BS_{|R}$ the Brier Score computed in the sub-sample of recessions, and $BS_{|E}$ the Brier Score computed in the sub-sample of expansions. Equation 6 is very useful for two reasons. First, it clarifies that the Brier Score is driven by periods of expansions, since the economy tends to spend most of its time in such a state: in our samples, ω_E equals 88% in the US and 87% in the Euro Area. Second, it allows to better understand if a predictor is

more informative about a state of recession or expansion. For example, in section 3 we leverage Equation 6 to argue that a deterioration in financial conditions is particularly informative about a state of recession.

An increasingly popular tool to assess the accuracy of recession forecasts is the Receiver Operator Characteristics (ROC) analysis - see Fawcett (2006) for a comprehensive review and Berge and Jordà (2011) for the first application to business cycle dating. The ROC is a powerful tool to assess the accuracy of a binary classifier which, to be applied in the context of nowcasting/forecasting recessions, requires the specification of a threshold to transform the estimated probability into a binary classification. This introduces the thorny issue of what threshold value to adopt. Moreover, transforming an estimated probability into a binary variable leads to a loss of useful information. Imagine to select a threshold of 90% to detect a state of recession: estimated probabilities of 89% and 1% will be equally classified as an expansion, thus disregarding the useful informational content embedded in the differential between the two estimates.

The preferred way to deal with the issue of having to specify a threshold in the ROC framework is to calculate the area under the ROC curve (AUROC), and use it to assess the accuracy of recession predictions. This metric computes the area underneath the curve connecting the true positive rate and the false negative rate of the probabilistic prediction for each possible value of the threshold. While the AUROC metric is a powerful way to determine the accuracy of a binary classifier, it is less so for a probabilistic prediction since, as pointed out in Fawcett (2006), *"a classifier need not produce accurate, calibrated probability estimates; it need only produce relative accurate scores that serve to discriminate positive and negative instances"*. In other words, the AUROC metric is scale-invariant and ignores whether a probabilistic forecast is well calibrated. Since our goal is to nowcast the *risk* of being in a recession, the Brier Score seems a more appropriate accuracy metric - for a comprehensive discussion of these issues see Lahiri and Yang (2013) and Lahiri and Yang (2023).

3 Main Results

Figure 3 summarizes our baseline estimates of recession risk in the United States (top panel) and in the Euro Area (bottom panel). This estimation is performed over the period 1980m1-2021m12 for the US and 1985m1-2021m12 for the Euro Area, and recession risk is estimated in-sample: we estimate the coefficients of our Bayesian logit over the full sample and then compute recession risk, using the latest available vintage of the predictors.

The figure reveals how our recession risk nowcast precisely identifies both the beginning and the end of recessions, for both geographical areas. The probabilistic nature of our nowcast also flags periods of economic turbulence that are not severe enough to be classified as a recession by the business cycle dating committees, such as most of 2012 in the US and the early 2000s in the Euro Area. This is not a failure of our nowcast, but a desirable feature that provides a more nuanced interpretation of uncertain economic times.
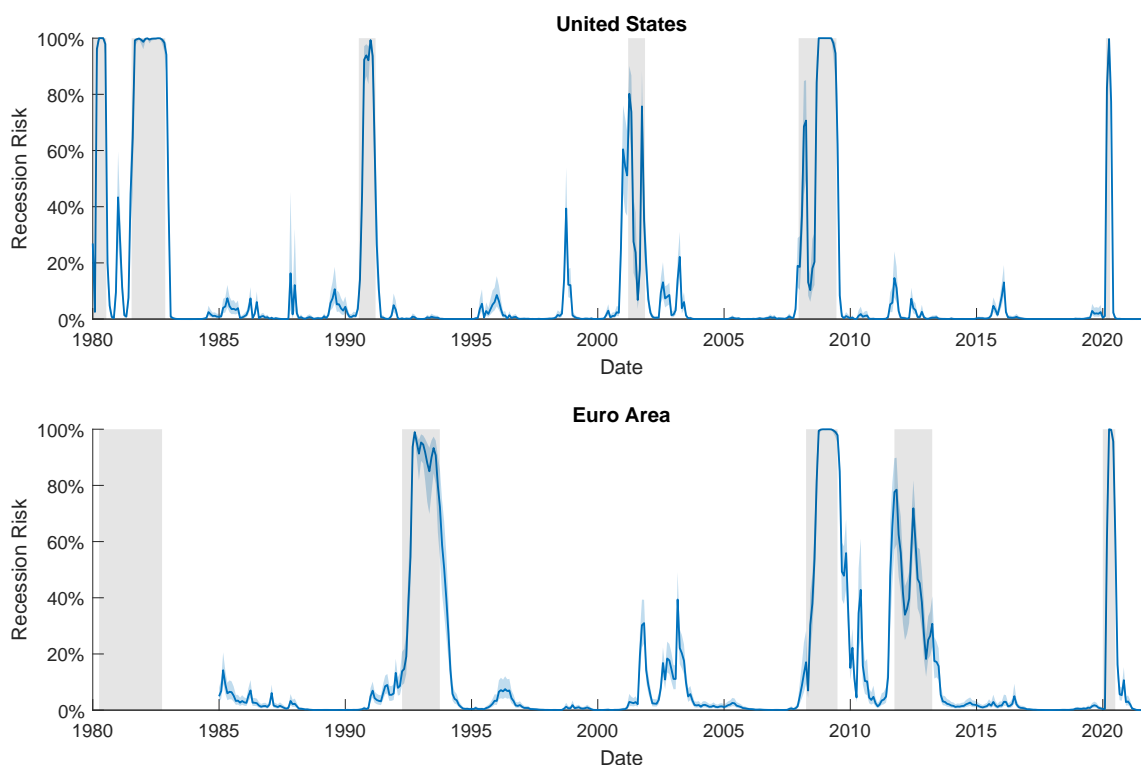

Figure 3: Recession Risk Nowcast for the US and the Euro Area
Note: In-sample estimates. Grey shaded bars correspond to official NBER and CEPR recessions. The solid line represents the median estimate, while the shaded bands represent 90% credible intervals.

Thanks to the inclusion of financial conditions, our nowcast is able to pick up early signals of distress encoded in asset prices. For example, it estimates a high recession risk in late 2008 when Lehman Brothers went bankrupt, a period which was later classified by the NBER as part of the Great Recession.

As informative as our in-sample estimates might be, however, our goal is to study the real-time properties of our nowcast. We therefore put ourselves in the shoes of a financial analyst who wants to perform the following exercise. The first business day after the month of reference closes, the analyst pulls the time-series

for the ESI, the PMI Manufacturing and the CISS. Then, the analyst estimates the coefficients of the Bayesian logit over the available sample discarding the last $d = 24$ months–to account for the announcement delay by the NBER and the CEPR. Once the model coefficients are estimated, the analyst feeds their posterior density and the latest value of the predictors into Equation 2 to obtain a real-time estimate of recession risk for the reference month. Thanks to the timeliness of our predictors, the analyst is able to estimate recession risk for–say–November on the first business day of December.

We implement this real-time evaluation as an expanding-window rolling (pseudo) out-of-sample estimation and the results are reported in Figure 4, where we also overlay the in-sample nowcast from Figure 3. Notice that the evaluation is a pseudo out-of-sample because we ignore the (minimal) revisions in the predictors.
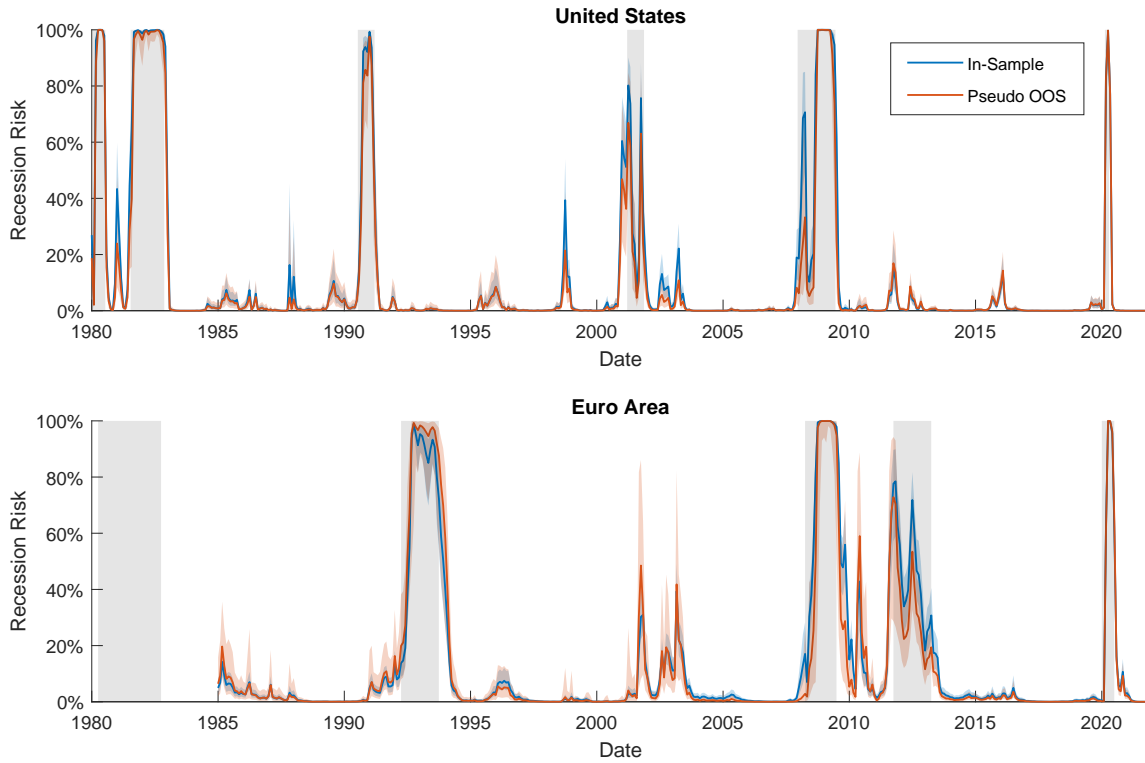

Figure 4: Recession Risk Nowcast - A (Pseudo) Real-Time Assessment
Note: In-sample estimates in blue, pseudo out-of-sample estimates in orange. The rolling out-of-sample estimation begins in 1995m1. Grey shaded bars correspond to official NBER and CEPR recessions. The solid line represents the median estimate, while the shaded bands represent 90% credible intervals.

Figure 4 shows the stability of our nowcast. The correlation between the in-sample and the pseudo out-of-sample estimates is 0.99 for the US and 0.98 for the Euro Area. The Brier Scores for the in-sample and out-of-sample estimates are 0.028 and 0.032 for the US, and 0.045 and 0.054 for the Euro Area, respectively. The stability of our nowcast should not come as a surprise: recessions are extreme events characterized by a material deterioration of macroeconomic and financial conditions. As a result, estimation revisions (which is what our exercise captures) do not alter the strong recessionary signal coming from our predictors.

Since our predictors are minimally revised, we expect our (pseudo) out-of-sample results to translate into real-time results. Amburgey and McCracken (2023) confirm the real-time predictive content of the Chicago

Fed's NFCI when using unofficial real-time vintages to estimate the growth-at-risk framework. While the CISS is not even revised, the finding suggests a very stable relation between the most popular measures of financial conditions and the distribution of GDP growth, even across data revisions.

We were also able to collect a few vintages of the Economic Sentiment Indicator (ESI) from the ECB real-time database built by Giannone, Henry, Lalik and Modugno (2012) and re-estimate recession risk across them. The results are reported in Figure 5, which confirms the stability of our estimates across the small revisions to the ESI. Even though we were not able to replicate the exercise for the PMI Manufacturing due to data limitations, revisions to its seasonal factors tend to be even smaller than those to the ESI.
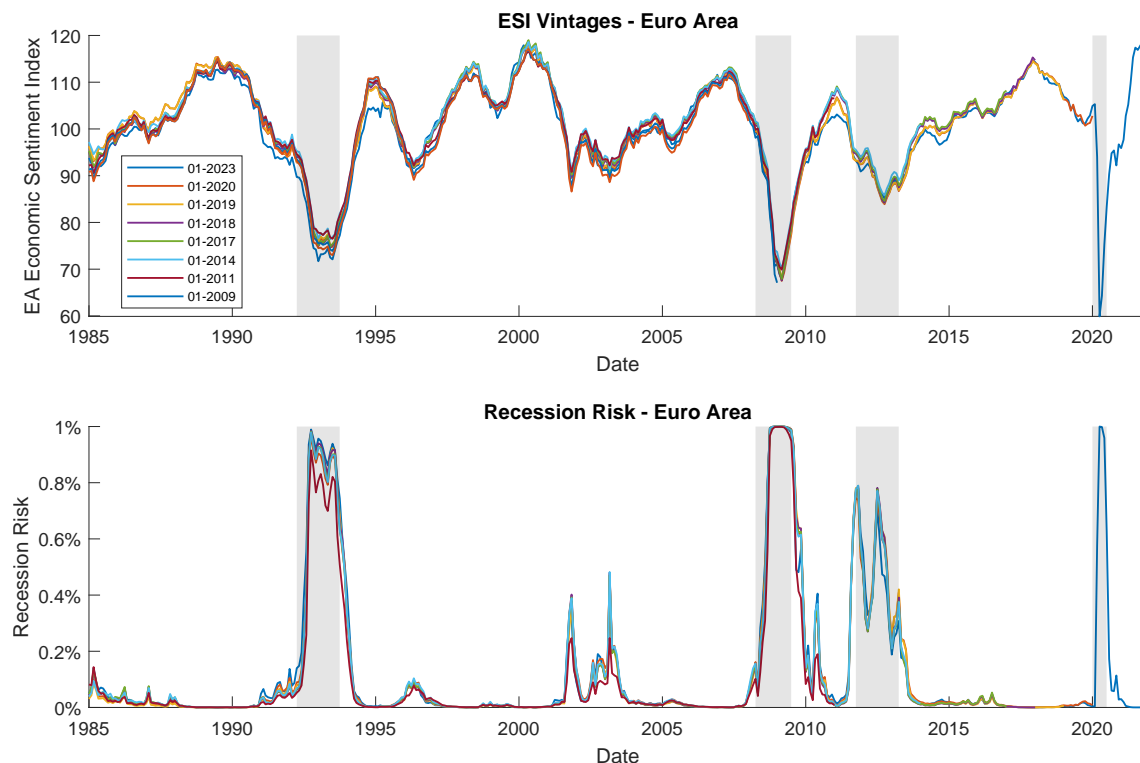

Figure 5: Recession Risk in the Euro Area - Revisions to the ESI
Note: In-sample estimates for each available vintage. Grey shaded bars correspond to official CEPR recessions.

Our nowcast is also robust to the econometric specification and the estimation method adopted. In Figure A1 in the Appendix, we show the robustness of our Bayesian logit when compared with: a probit and a logit specification estimated with maximum likelihood; a "dynamic" probit specification which includes a lag of the dependent variable; a non-parametric Nadaraya-Watson specification with a Gaussian product kernel and unit bandwidth. Moreover, in Figure A2 we show that even a simple a linear probability model estimated with OLS exhibits a strong comovement with our baseline estimates.

3.1 The Importance of Financial Conditions

To better understand the ability of financial conditions to summarize the current state of the economy, we re-estimate our nowcasting model using one predictor at a time. The results are reported in Figure 6 for the US, and in Figure A3 for the Euro Area. The top panel reports our recession risk nowcast using both

predictors, while the bottom panel reports it when using one predictor at a time.
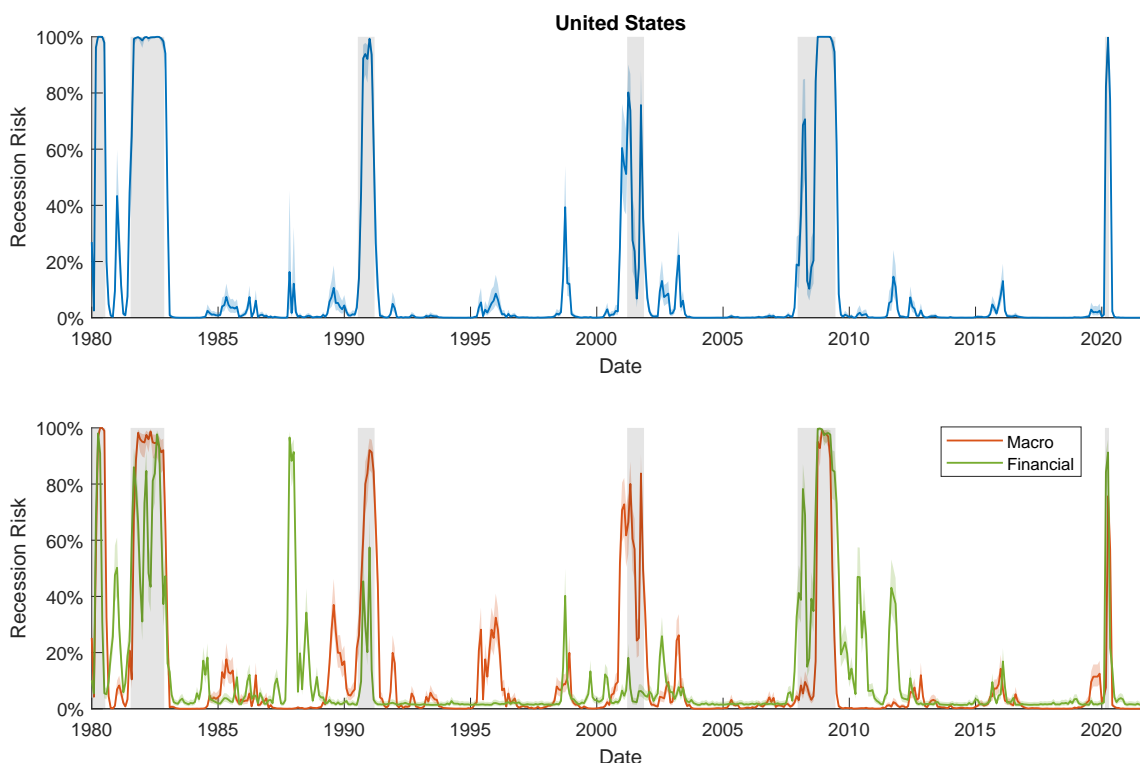

Figure 6: Macro vs Financial Predictors for US Recession Risk
Note: In-sample estimates. Grey shaded bars correspond to official NBER recessions. The solid line represents the median estimate, while the shaded bands represent 90% credible intervals.

The first lesson from Figure 6 is that macroeconomic and financial conditions tend to provide complementary pieces of information. For example, financial conditions are what allows the model to estimate a high probability of recession risk in late 2008, several months before the recession showed up in macroeconomic data. Another example is given by the early 2000s, which saw a deterioration in macroeconomic data but not in financial conditions. The episode was later classified by the NBER dating committee as a recession after a long period of scrutiny during which data revisions sent mixed messages on the state of the economy. Similar conclusions on the relative role of macroeconomic and financial predictors can be drawn for the Euro Area.

Figure 7 reports the Brier Score and its two-way decomposition for each nowcast. While a macroeconomic predictor such as the PMI or the ESI outperforms financial conditions when nowcasting recession risk, adding financial conditions to macroeconomic data boosts accuracy by more than 20%. The decomposition in Equation 5 helps us understand why. While the "calibration" component of the Brier Score is almost unchanged when financial conditions are included, the "refinement" component - which measures the ability to separate recessions from expansions - is significantly reduced. In other words, financial conditions contain additional valuable information on the state of the economy, probably because financial prices incorporate information not yet reflected in standard macroeconomic data.
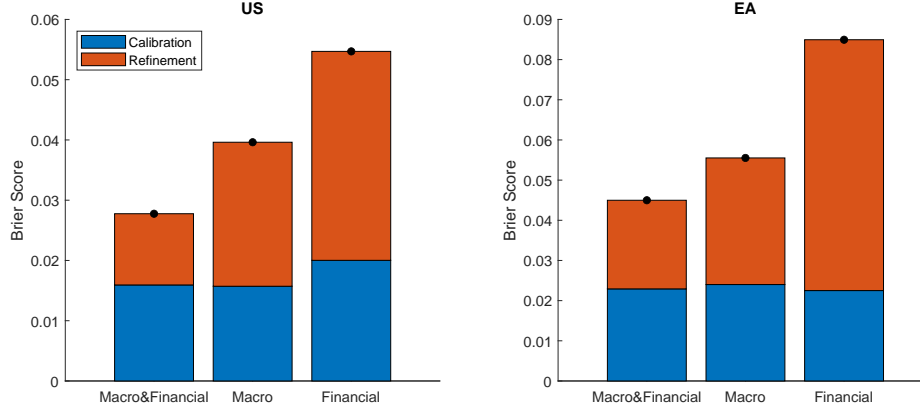
Figure 7: Financial Conditions Help Refine Recession Risk Estimates
Note: A lower Brier Score corresponds to higher ability to predict recessions. The black dot represent the overall Brier Score, while the blue and orange bars are an exact decomposition thereof. Scores computed using the posterior median of our in-sample nowcasts.

We then leverage the decomposition from Equation 6 to better understand whether financial conditions have a relative advantage at identifying periods of recession or expansion. Table 4 reveals how adding financial conditions improves the accuracy of our nowcast particularly during recessions. This makes intuitive sense: a decline in the health of the financial system is tightly connected to downside risk to growth, and therefore helps identify periods of recession.

Table 4: Brier Scores across Recessions and Expansions

	United States			Euro Area		
Brier Score	**Macro&Financial**	**Macro**	**Financial**	**Macro&Financial**	**Macro**	**Financial**
Recession ($BS_{|R}$)	0.167	0.253	0.345	0.234	0.311	0.535
Expansion ($BS_{|E}$)	0.010	0.012	0.017	0.017	0.018	0.019
Overall (BS)	0.028	0.040	0.055	0.045	0.056	0.085

Note: The Brier Scores in Recession and in Expansion do not aggregate to the Overall Brier Score without applying the weights from Equation 6 first. Scores computed using the posterior median of our in-sample nowcasts.

3.2   Alternative Predictors

Given the vast set of available economic and financial predictors, it is natural to wonder how our preferred predictors fare against others. To this end, we collect some of the most followed macroeconomic and financial variables by financial participants and economists in the US, and estimate our nowcasting model using each one of them at a time. We then compute the associated Brier Scores, and report the results in Figure 8.
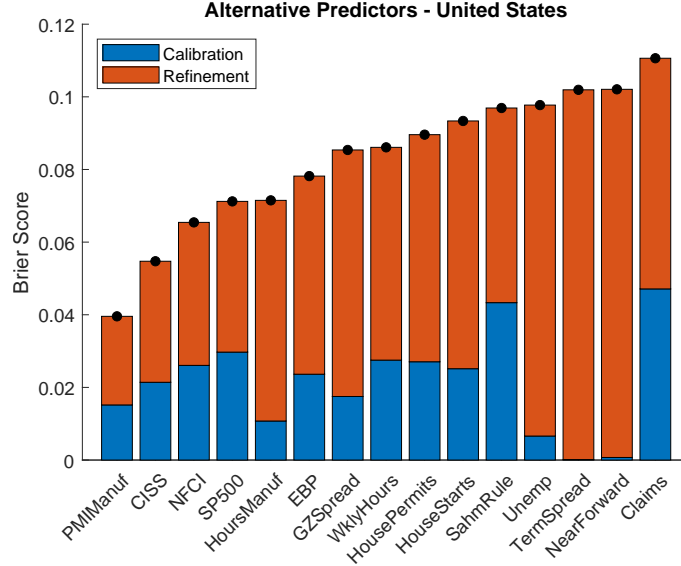
Figure 8: Alternative Predictors for US Recession Risk
Note: In-sample estimates, posterior median.

We consider the Chicago Fed National Financial Condition Index (NFCI), the one-year change in the S&P500, total hours worked in the manufacturing sector, the excess bond premium and the credit spread from Gilchrist and Zakrajšek (2012), average weekly hours of all employees, housing permits and starts, the Sahm-rule's unemployment rate transformation, the unemployment rate, the near-forward spread, the term spread, and jobless claims. Both the ISM PMI Manufacturing and the CISS, on the left, turn out to produce the most accurate nowcast. Moreover, these alternative predictors are subject to larger revisions and longer publication delays than our preferred ones, making them less useful in a real-time application.

A promising direction is to use statistical methods to combine or select these different predictors, along the lines of Ajello, Cavallo, Favara, Peterman, Schindler IV and Sinha (2023), who aggregate various measures of financial conditions using weights based on the predictive content for the central tendency of growth. In an application to stock price returns, Crump et al. (2020a) aggregate predictions based on the informative content for the overall predictive density, while Opschoor, Van Dijk and van der Wel (2017) focus on the informative content for value at risk. Our results suggest an alternative strategy of weighting predictors based on their information content for recession risk.

3.3 Comparison with Unemployment Rate Rules

A widely followed indicator used to call recessions in real-time is the unemployment rate, and transformations thereof. This is due partly to its high frequency and short publication lag, and partly to the observation that abrupt increases in unemployment have historically coincided with the beginning of a recession–see Crump et al. (2020b) for an overview.

A popular approach to call recessions in real-time is to take (a transformation of) the unemployment rate and apply a "threshold rule": whenever the preferred transformation of unemployment exceeds a given threshold value, the economy is considered in a recession. While there are various formalizations of this

idea–e.g. Stock and Watson (2010) and Barnichon, Nekarda, Hatzius, Stehn and Petrongolo (2012)–a popular version of this rule is due to Sahm. The so-called "Sahm-Rule" posits that the economy enters a recession whenever the three-month average of the unemployment rate minus the low of the unemployment rate over the last 12 months is greater than 0.5. In Figure 9 we compare our nowcast (top panel) with the Sahm-Rule's transformation of the unemployment rate (bottom panel). The bottom panel of the figure also reports a dashed line corresponding to the 0.5 threshold value of the Sahm-Rule.
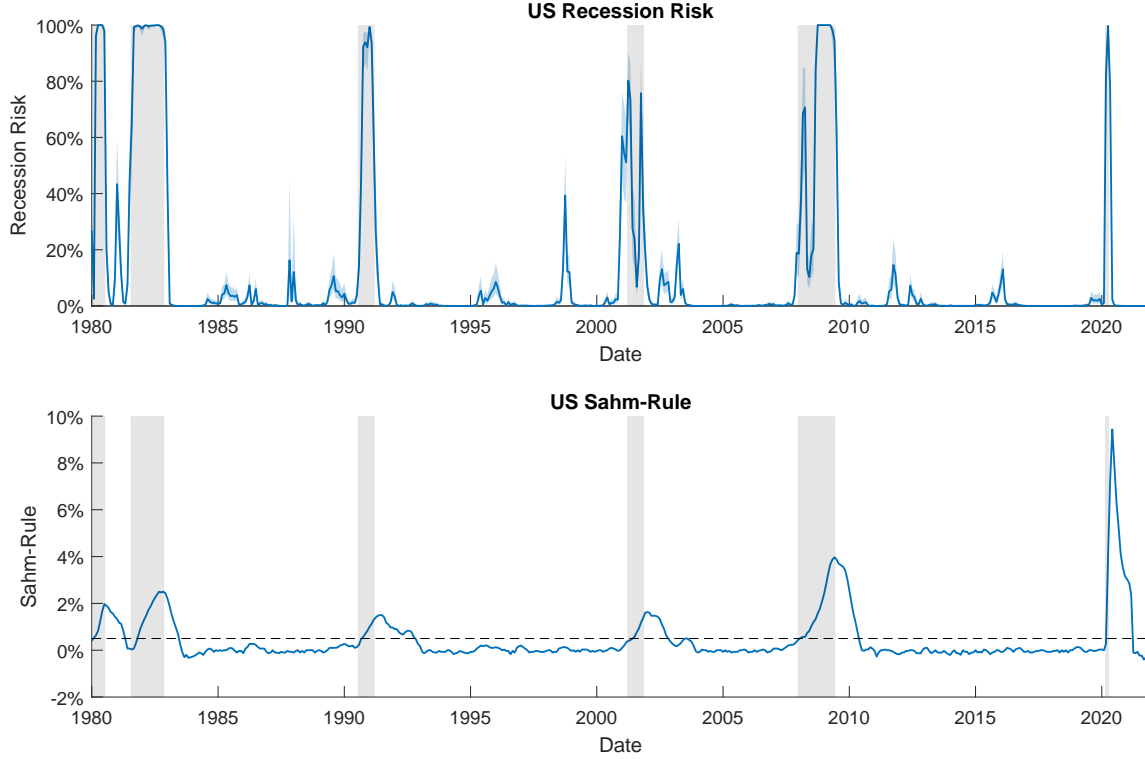

Figure 9: Comparison with the Sahm-Rule
Note: Grey shaded bars correspond to official NBER recessions. Top panel: In-sample estimates; the solid line represents the median estimate, while the shaded bands represent 90% credible intervals. Bottom panel: the solid blue line represents the Sahm-Rule's transformation of the unemployment rate, while the dashed black line representes the 0.5 threshold.

The figure suggests two conclusions. First, both our nowcast and an unemployment-based rule accurately identify the beginning of a recession, with our nowcast being slightly more timely. Second, our nowcast proves more useful at detecting the end of a recession and the beginning of a recovery. This is probably due to the lagging dynamics of the labor market, which tends to improve only after the recovery is already underway.

3.4 Nowcasting vs Forecasting Recession Risk

Predicting the present is easier than predicting the future, and this principle applies to recession risk too. To illustrate this point, we rewrite Equation 3 as

$$Y_{t+h}|X_t, \beta \sim_{iid} Bern\left(\frac{\exp(X_t \cdot \beta)}{1 + \exp(X_t \cdot \beta)}\right) \tag{7}$$

which now assumes that the predictors in month t contain information about recession risk h months ahead. Equation 7 also clarifies that our nowcasting exercise is closely related to a long-standing literature whose goal is to *forecast* future recessions using logit and probit models - see Hamilton (2011) for an overview.
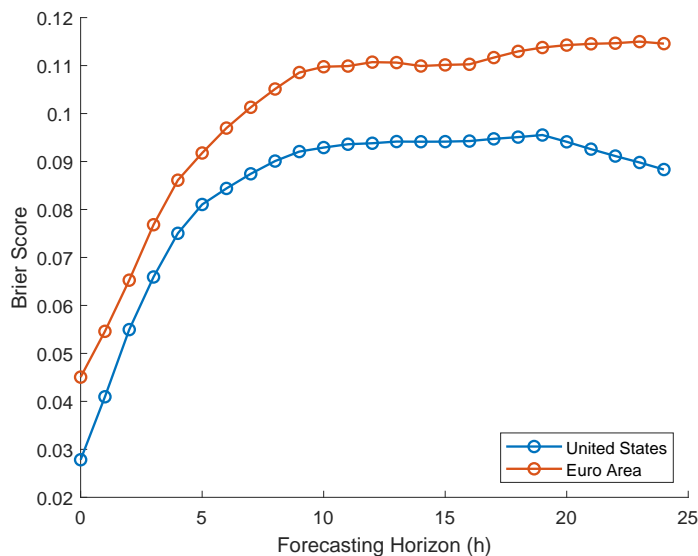

Figure 10: Nowcasting vs Forecasting Recession Risk
Note: In-sample estimates, posterior median.

Here, we estimate Equation 7 and compute the Brier Score for each value of $h \in [0, 24]$, where $h = 0$ represents our nowcasting exercise and $h > 0$ represents a forecasting exercise. The results are displayed in Figure 10 and illustrate how the accuracy of our predictors quickly deteriorates in the forecasting horizon. The accuracy of recession forecasts quickly deteriorates in the forecasting horizon also for professional forecasters in the US. Lahiri and Wang (2013) show how forecasts of the probability of a GDP decline in the Survey of Professional Forecasters display accuracy only in the short-term, i.e. between zero and two quarters ahead.

4   Recession Risk and Growth-at-Risk

There is a close and intuitive connection between recession risk and the growth-at-risk framework proposed by Adrian et al. (2019). Indeed, official recession dates almost perfectly overlap with two consecutive quarters of negative growth–which is where the notion of "technical recession" used by the specialized press stems from and which can be also formalized by the BBQ algorithm proposed by Harding and Pagan (2002). We thus take the two-quarter change in real GDP growth

$$Z_{t_q} \equiv \frac{X_{t_q} - X_{t_q-2}}{X_{t_q-2}},$$

where X_{t_q} is real GDP in quarter t_q, and call a recession whenever this growth rate takes a negative value. This simple rule dates recessions and expansions similarly to the business cycle dating committees in both the US and the Euro Area. In other words:

$$Y_{t_q} \approx \mathbb{1}(Z_{t_q} \leq 0)$$

where Y_{t_q} is the official recession dummy at quarterly frequency. This implies that recession risk can be thought of as the cumulative distribution function (CDF) of real GDP growth evaluated at 0:

$$\mathrm{Prob}(Y_{t_q} = 1) \approx \mathrm{Prob}(Z_{t_q} \leq 0)$$

so that one can use any of the many available tools to estimate conditional CDFs to construct a recession risk nowcast. Importantly, the connection between recession risk and the growth-at-risk framework becomes now obvious: the conditional CDF of GDP growth evaluated at 0 corresponds, most of the time, to a low quantile of the GDP growth distribution in Adrian et al. (2019). As a result, our recession risk nowcast is another way of thinking about the growth-at-risk framework: while the latter fixes the size of the tail and finds the growth rate of GDP associated to that tail, the former fixes the growth rate of GDP and measures the size of the tail. To estimate our recession risk as a conditional CDF, we assume that

$$\mathbb{1}(Z_t \leq 0)|X_t, \beta \sim_{iid} \mathrm{Bern}\left(\frac{\exp(X_t \cdot \beta)}{1 + \exp(X_t \cdot \beta)}\right)$$

and leverage our Bayesian logit by replacing the dependent variable. Since GDP in a given quarter is not released until the following quarter, for each quarter of interest we estimate the coefficients of the conditional CDF using data up to the previous quarter, and then feed the average value of the predictors in the quarter of interest. For the US, we collect real-time vintages of real GDP from the Federal Reserve Bank of Philadelphia database created by Croushore and Stark (2001). For the Euro Area, we do not use real-time vintages, but we backdate the official Eurostat's GDP data using the Area Wide Model database by Fagan, Henry and Mestre (2005). To compare these GDP-based estimates with our previous results based on official recession dates, we need to transform the monthly out-of-sample nowcasts from Figure 4 into quarterly, and we do so by taking the average recession risk during the quarter. The results are reported in Figure 11.
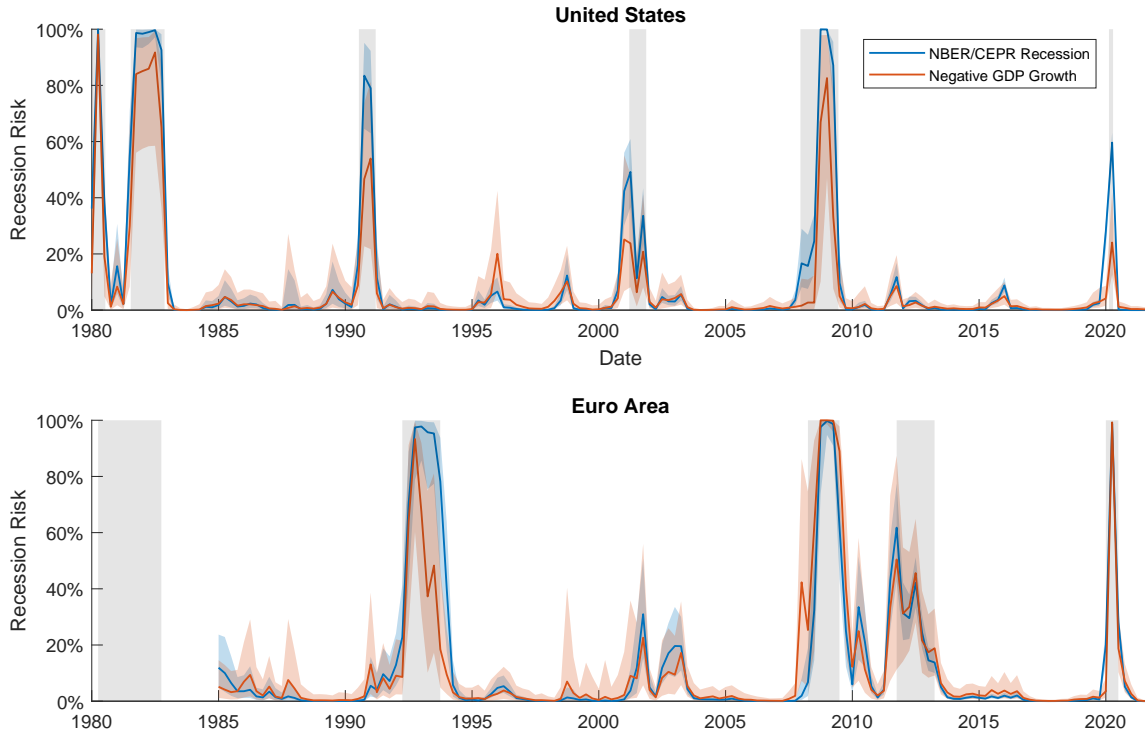
Figure 11: Recession Risk Coincides with Downside Risk to GDP Growth
Note: Grey shaded bars correspond to official NBER and CEPR recessions. The solid lines represent median estimates, while the shaded bands represent 90% credible intervals.

The correlation between the two sets of estimates is 0.96 for the US and 0.90 for the Euro Area, confirming our initial conjecture: recession risk is, indeed, downside risk to GDP growth.

It is also possible to go a step further and estimate the entire conditional CDF. This is what we do for the US in Figure 12, where we estimate it using three approaches: our Bayesian logit; a Nadaraya-Watson non-parametric regression with a Gaussian product kernel and unit bandwidth; and the non-parametric conditional CDF estimator with optimal bandwidth proposed by Li, Lin and Racine (2013).
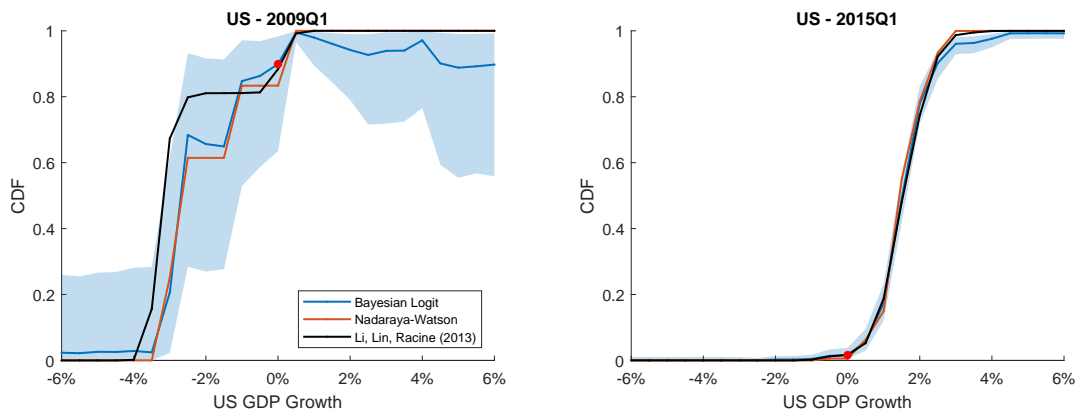

Figure 12: Recession Risk and the Full GDP Growth Distribution
Note: In-sample estimates.

The figure focuses on two episodes, one in which the economy is experiencing a recession, and one in which

it is experiencing an expansion. The left panel of the figure focuses on a quarter in the middle of the Great Recession, and thus estimates a distribution of GDP growth which is almost entirely on the negative part of its support. The conditional CDF evaluated at zero (highlighted with a red dot) is close to one: the nowcast suggests a very high risk of recession. The right panel, instead, focuses on a quarter of expansion: the US economy is experiencing robust growth and, as a result, the distribution of GDP growth is almost entirely on the positive part of its of support. The CDF evaluated at 0 is close to zero, and so is recession risk. The estimates are stable across specifications, and it is particularly impressive how well the Bayesian logit fares given that it does not impose monotonicity during estimation of the CDF.

5 Comparison with Professional Forecasters

In this section, we benchmark our nowcast with the Survey of Professional Forecasters (SPF) for the US. Every quarter, the SPF asks respondents to provide an estimate of the probability of a quarter-over-quarter decline in real GDP for the current quarter (the quarter in which the survey is distributed), one quarter ahead, two quarters ahead, three quarters ahead, and four quarters ahead - Lahiri and Wang (2013) provide a comprehensive assessment of these SPF questions. The probability of negative growth one quarter ahead is commonly referred to as the "Anxious Index" and these questions on the probability of a GDP decline are commonly used as proxies for recession probabilities.

Given that our goal is to nowcast recession risk, the SPF question relevant for us is the one that relates to the probability of a real GDP decline in the quarter the survey is taken. The SPF is published in the second month of the quarter and survey respondents are able to observe economic data for the first month. This implies that the SPF question is actually a forecast, given that the second and the third months of the quarter have not realized when the question is asked. To align our nowcast with the SPF question, we take our (pseudo) out-of-sample nowcast for the US from Figure 4 and consider only the first month of the quarter as our quarterly forecast. This is because an analyst using our nowcast to forecast the entire quarter at the beginning of the second month (i.e., when the SPF is taken) would be able to see the PMI Manufacturing and the CISS only for the first month of the quarter. The results are reported in Figure 13.

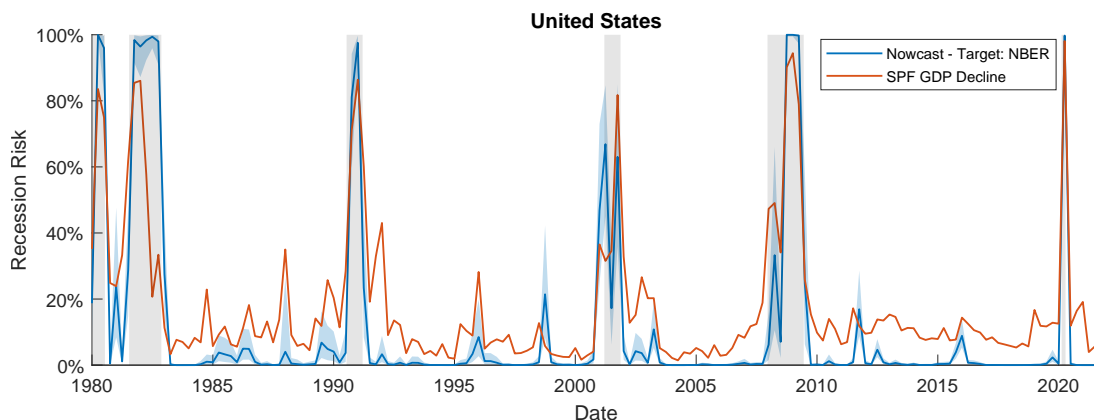**Figure 13:** Recession Risk Nowcast vs Professional Forecasters
Note: Grey shaded bars correspond to official NBER recessions.

The probabilities from the SPF and our nowcast both spike during recessions, suggesting a similar ability

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to identify downturn. Surprisingly, however, professional forecasters seem to over-estimate recession risk during periods of expansion. A valid objection to our exercise is that professional forecasters are not asked about recession risk, but about the probability of a decline in real GDP. We thus re-estimate our nowcast replacing NBER recessions with a dummy denoting a quarter-over-quarter decline in real GDP, thus aligning the target of our nowcast with the target of the forecasters. Similarly to what we did in section 4, we estimate our nowcast using real-time GDP vintages from the Federal Reserve Bank of Philadelphia as follows. In a given quarter, we estimate the model coefficients using data up to the previous quarter (since GDP for the current quarter has not been released yet). Then, we feed the PMI Manufacturing and the CISS for the first month of the current quarter into Equation 2 to estimate recession risk for the current quarter. The results are summarized in Figure 14, where the grey shaded bars reflect quarters in which real GDP declined (on a quarter-over-quarter basis).
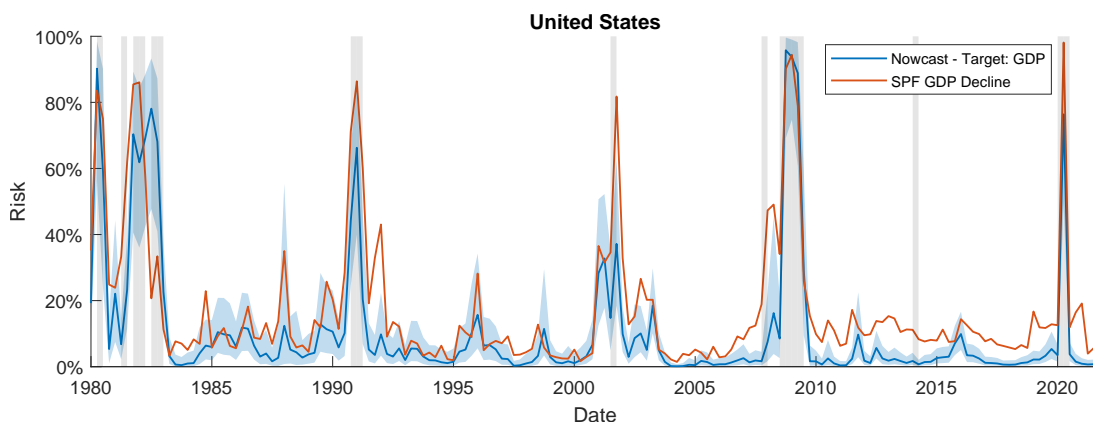

Figure 14: Real GDP Decline Nowcast vs Professional Forecasters
Note: Grey shaded bars denote a quarter-over-quarter decline in real GDP, measured using the real-time vintages from a year later (e.g. the value in 2000q1 is the vintage available in 2001q1).

Visual inspection of the figure seems to support the same conclusion drawn before: the SPF and our nowcast appear to have a similar ability to identify declines in real GDP, but the professional forecasters tend to over-estimate the probability of a decline during expansions. To formally quantify this point, we compute Brier Scores for both exercises in Table 5 below. The first two columns report Brier Scores for the nowcast and the SPF for Figure 13, while the last two columns do the same for Figure 14.

Table 5: Nowcast vs Professional Forecasters

	Target: NBER Recession		Target: Real GDP	
Brier Score	**Nowcast**	**SPF**	**Nowcast**	**SPF**
Recession ($BS_{|R}$)	0.202	0.210	0.356	0.283
Expansion ($BS_{|E}$)	0.006	0.023	0.014	0.036
Overall (BS)	0.029	0.045	0.048	0.061

Note: The Brier Scores in Recession and in Expansion do not aggregate to the Overall Brier Score without applying the weights from Equation 6 first. The target for the Brier Score under the header "Target: NBER Recession" is the official NBER recession dummy, while under the header "Target: Real GDP" is the real GDP decline dummy constructed using real-time vintages from a year later.

Our nowcast appears to be more accurate than the SPF, both when the target are NBER recessions and when

the target is a decline in real GDP. The decomposition from Equation 6 further clarifies that our nowcast is as good as the SPF at detecting declines in economic activity, but it attributes a lower probability of decline during expansions. A promising venue for future research is to combine model-based and survey-based forecasts to leverage the relative merits of each and improve overall accuracy–as in Adams et al. (2021) among others.

6 Conclusions

We have built a simple yet robust framework to nowcast recession risk at a monthly frequency in both the US and the Euro Area. One of the main insights from this chapter is that financial conditions contain information about the *current* state of the economy that complements the information from more standard (macro)economic indicators. Another important insight is that recession risk is fundamentally downside risk to GDP growth, which most of the time corresponds to a low quantile in the growth-at-risk framework proposed by Adrian et al. (2019). Moreover, thanks to its simplicity, our nowcast can be easily extended to several other economies. In fact, the CISS and the ESI are available for Euro Area member countries, and comparable indicators can be put together for countries such as the UK, Canada, and Japan.

We see several avenues for future research. One relates to the econometric specification adopted to nowcast recession risk. While we opted for a simple and parsimonious logit specification coupled with a careful selection of predictors, another route is to specify a larger and/or more structural model. One route could be to retain the logit/probit specification and augment it with a factor structure to enlarge the set of predictors considered as done by Bellégo and Ferrara (2012) to forecast recessions in the Euro Area, or with a mixed-frequency structure to understand the impact of high-frequency predictors on low-frequency events, as in Galvão and Owyang (2022). Other routes involve building a factor model–as in Stock and Watson (1989)–a Markov-Switching model–as in Hamilton (1989), Chauvet and Hamilton (2006)–or a combination of both–as in Chauvet (1998), Chauvet and Piger (2008), Doz and Petronevich (2016), Doz, Ferrara and Pionnier (2020)– and explicitly introduce financial conditions as predictors. The results in Adrian et al. (2019) and in this chapter suggest that having switching probabilities depend on financial conditions should improve the ability of the model to correctly identify the state of the economy–as in Caldara, Cascaldi-Garcia, Cuba-Borda and Loria (2021a). Models in which the conditional variance and the conditional mean of GDP move in opposite directions as a function of financial conditions also seem promising tools to nowcast recession risk. A few papers have explored this insight–suggested by Adrian et al. (2019)–in autoregressive models with stochastic volatility: some recent examples are Carriero, Clark and Marcellino (2020), Caldara, Scotti and Zhong (2021b), Adrian, Duarte and Iyer (2023).

Another promising direction involves exploring the role of financial conditions further. In this chapter, we leverage the CISS indicator which combines five financial segments: bonds, equities, money markets, foreign exchange markets, financial intermediaries. Other studies have looked at credit spreads and the slope of the yield curve to forecast economic activity–for instance, see Favara, Gilchrist, Lewis and Zakrajšek (2016). A natural follow-up questions is whether one of these measures better encodes information on the state of the economy. Another question is whether additional dimensions of the financial system can help better understand the current state of the economy–for example, Boyarchenko et al. (2020) examine the relation between bank capital and the distribution of GDP growth.

Finally, the digital revolution is opening new exciting frontiers thanks to the availability of high-frequency data from various domains, also known as "alternative data". An example is internet search data, which can be used to augment real-time business cycle dating–among others, Ferrara and Simoni (2023) leverage Google search data to nowcast GDP. Another example is given by natural language processing (NLP), which leverages increasingly more sophisticated techniques to construct quantitative measures out of unstructured text data. A couple of papers connecting the distribution of GDP growth to text-based predictors are Hengge (2019) and Sharpe, Sinha and Hollrah (2023). Thanks to recent progress in Large Language Models (LLMs) and Generative-AI, our ability to process vast amount of existing textual data will increase significantly and will lead to the discovery of new insights. High-frequency transactions also present an exciting opportunity to measure economic activity at a much higher frequency than it was ever possible before. For example, Buda, Hansen, Rodrigo, Carvalho, Ortiz and Rodríguez Mora (2023) aggregate credit card data to successfully approximate official consumption statistics for the Spanish economy.

Finally, while this chapter focuses on recessions, the methodologies discussed can be also used to nowcast and forecast other important events. One example could be financial crises in specific countries or geographical areas, where data from the cross-section of countries can partially offset the low frequency at which large but important events occur.

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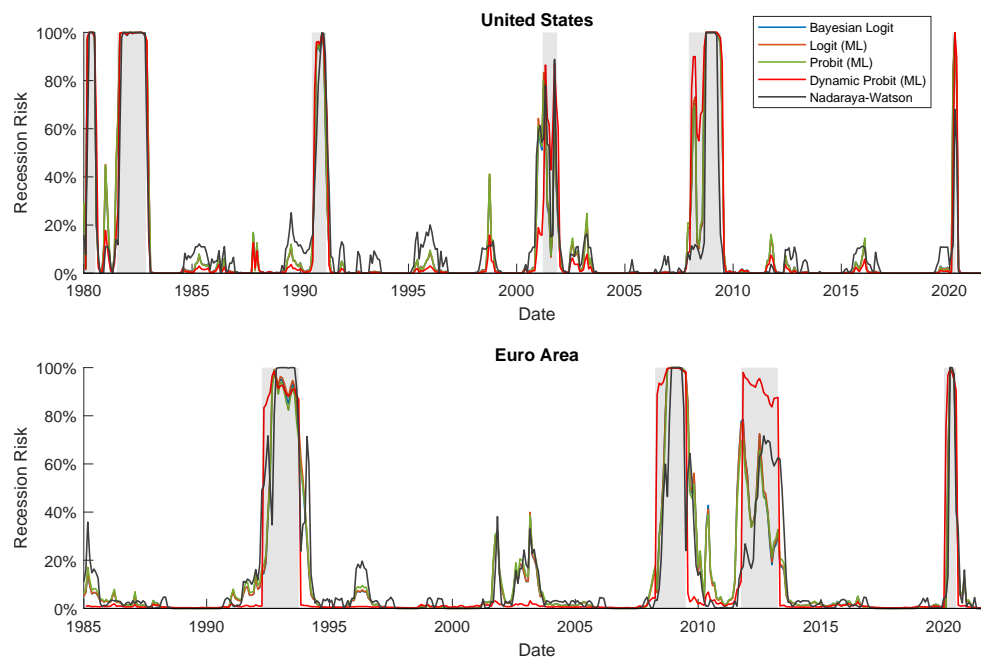
A Appendix

A.1 Additional Results

Figure A1: Robustness to Econometric Specification and Estimation Method
Note: In-sample results. Grey shaded bars correspond to official NBER and CEPR recessions.
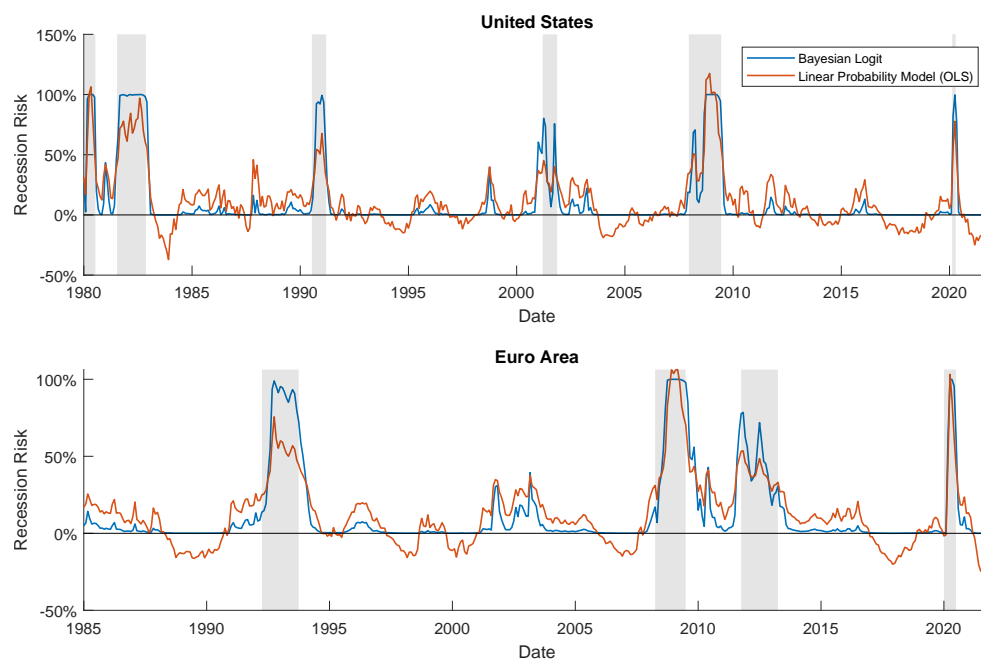

Figure A2: Robustness to Linear Probability (OLS) Specification
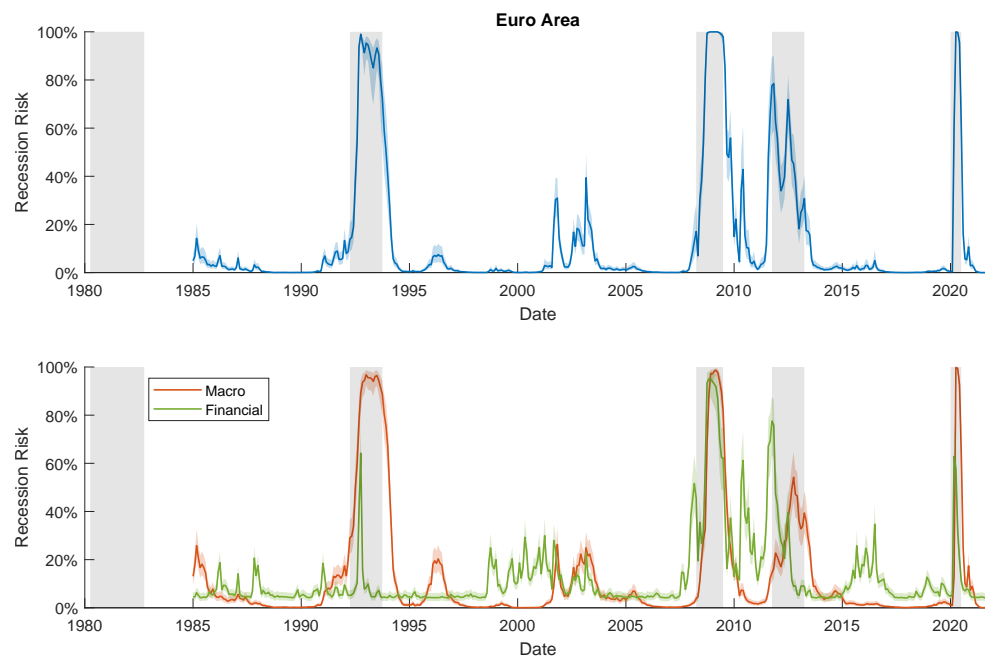**Note**: In-sample results. Grey shaded bars correspond to official NBER and CEPR recessions.

Figure A3: Macro vs Financial Predictors for EA Recession Risk
Note: In-sample results. Grey shaded bars correspond to official CEPR recessions.