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Forecasting US recessions: The role of sentiment ☆

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ABSTRACT

We study the role of sentiment variables as predictors for US recessions. We combine sentiment variables with either classical recession predictors or common factors based on a large panel of macroeconomic and financial variables. Sentiment variables hold vast predictive power for US recessions in excess of both the classical recession predictors and the common factors. The strong importance of the sentiment variables is documented both in-sample and out-of-sample.

1. Introduction

The monthly releases of consumer and business sentiment surveys attract widespread attention from policy makers, investors, and the media, and are among the most watched indicators of future economic activity, especially during times of economic crisis. Former Chairman of the Board of Governors of the Federal Reserve System Ben S. Bernanke expresses the importance of confidence in the following way: "*As in all past crises, at the root of the problem is a loss of confidence by investors and the public in the strength of key financial institutions and markets.*"[1]

The presumption that business and consumer sentiment variables are related to the state of the economy is substantiated by Fig. 1 in which we plot indices of business and consumer sentiment (denoted PMI_t and CC_t, respectively) against NBER defined recession periods marked by grey shading. Around each recession period the sentiment variables drop, which is consistent with bad sentiment typically reflecting poor economic conditions. Thus, Fig. 1 highlights the procyclical movements of both sentiment indices in relation to the business cycle.

Sentiment variables have long been thought to contain information about future fluctuations in the level of real economic activity. Matsusaka and Sbordone (1995) show that consumer sentiment adds significant information in forecasting GDP and Batchelor and Dua (1998) find that forecasts of GDP during the 1991 recession could have been improved had forecasters taken consumer confidence into account. Carroll et al. (1994), Bram and Ludvigson (1998), Howrey (2001), and Ludvigson (2004) show that measures of consumer sentiment contain information about consumer spending. Howrey (2001) also considers the relationship between consumer confidence and the business cycle. Similarly, Dasgupta and Lahiri (1993) show that the Purchasing Manager's Index (PMI) is useful for forecasting GDP changes. Additionally, Kauffman (1999), Klein and Moore (1991), Lindsey and Pavur (2005), Banerjee and Marcellino (2006) and Lahiri and Monokroussos (2013) show that business sentiment is useful for forecasting and nowcasting GDP and the business cycle. As pointed out by Koenig (2002), the use of sentiment indices has two important advantages for forecasting compared to alternative leading indicators. In particular, they are available in real-time and are

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[1] Quotation from speech by Bernanke (2008).

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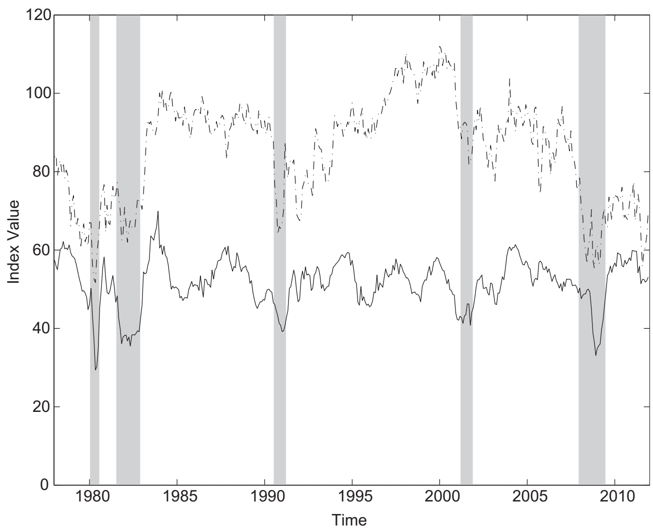

Fig. 1. Business and consumer confidence. This figure plots the time series of business confidence (PMI_t; solid line) and consumer confidence (CC_t; broken line) against NBER defined recession dates in grey shading.

not subject to subsequent revisions. Lahiri and Monokroussos (2013) note that no economic variables of similar importance are available with the same timeliness. Macroeconomic variables, in contrast, are typically published with a delay and are often subject to considerable revisions following the initial publication.

This paper separates itself from the extant literature by using sentiment variables to forecast a binary recession indicator using probit models rather than forecasting continuous variables such as GDP growth. A general finding with this approach is that the term spread, the short rate, and the stock market return carry important information about future recessions (Dueker, 1997; Estrella and Mishkin, 1998; Wright, 2006; Kauppi and Saikkonen, 2008; Nyberg, 2010). We add to the existing literature by showing that sentiment variables have considerably better forecasting power for future recessions than these classical recession predictors. In particular, we find that business sentiment is by far the single best recession predictor among the considered forecasting variables. Moreover, we find that combining sentiment variables with the classical recession predictors provides for stronger forecasting performance for future recession periods, both in-sample and out-of-sample.

Evidence of incremental predictive power of the sentiment variables could, however, simply be a result of the exclusion of other relevant economic control variables. To account for this concern, we examine the ability of sentiment variables to predict future recessions when controlling for a large panel of more than 150 macroeconomic and financial time series. This is done in an efficient way using a common factor approach (Stock and Watson, 2002a; Stock and Watson, 2002b; Bai and Ng, 2002; Bai and Ng, 2006). We find that the predictive power of the sentiment variables remain strong even in the presence of the common factors.

An important concern in forecasting is the issue of temporal instabilities in the parameters of the forecasting model. In particular, Stock and Watson (2003), Ng and Wright (2013), and Rossi (2013) find compelling evidence of temporal instabilities in a large proportion of linear models used to predict economic growth. In contrast, we find no evidence of instabilities in the predictive relationship between the binary recession indicator and models using sentiment variables as predictors. This finding is in line with Estrella et al. (2003) who find evidence of binary models being more stable than continuous models.

Overall, we find that sentiment variables are strong predictors for future recessions and that combining them with either classical recession predictors or with latent common factors significantly boost the predictive power.

The rest of the paper is structured as follows. Section 2 describes the econometric methodology. Section 3 introduces the data. Section 4 presents the empirical results, both in-sample and out-of-sample. Section 5 provides robustness analysis, while Section 6 concludes. Various details are delegated to the Appendix.

2. Econometric methodology

This section describes the econometric methodology. We first describe the probit model and its estimation. Second, we discuss the evaluation measures used to assess model performance. Lastly, we discuss the estimation of latent common factors from our panel of economic variables.

2.1. The model

Consider the binary-valued time series process $\{y_t\}_{t=1}^{T}$ that depends on the state of the economy as follows

$$y_t = \begin{cases} 1, & \text{if the economy is in a recession at time } t \\ 0, & \text{if the economy is in an expansion at time } t \end{cases} \tag{1}$$

The recession indicator y_t has, conditional on the information set $\mathcal{F}_{t-1}$, a Bernoulli distribution with probability parameter p_t, i.e. $y_t|\mathcal{F}_{t+1} \sim \mathcal{B}(p_t)$. Our aim is to model the conditional probability p_t of a future recession. To do so, we consider a standard probit model in which the conditional probability for the recession event $\{y_t = 1\}$ satisfies

$$\mathbb{E}_{t-1}[y_t] = \mathbb{P}_{t-1}[y_t = 1] = \Phi(\pi_t) = p_t \tag{2}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, which ensures that the conditional probability takes values in the unit interval $[0, 1]$, $\mathbb{E}_{t-1}[\cdot]$ and $\mathbb{P}_{t-1}[\cdot]$ denote, respectively, the conditional expectation and probability, and π_t is a linear function of variables in $\mathcal{F}_{t-1}$.[2] In particular, we consider nested specifications of π_t of the following form

$$\pi_t = \varpi + s'_{t-k}\alpha + z'_{t-k}\beta + f'_{t-k}\gamma \tag{3}$$

where s_{t-k} is a vector of sentiment variables, z_{t-k} is a vector containing classical recession predictors, and f_{t-k} is a vector of common factors representing information from a large panel of economic variables. Hence, with this specification, we control for a much richer information set compared to prior studies in which only a few observed variables are used as controls. This is important because by conditioning on a rich information set, it is possible to examine to what extent sentiment variables contain independent incremental explanatory power not captured by other economic predictors. The parameters of the probit model can be straightforwardly estimated using maximum likelihood estimation, and misspecification robust standard errors can be obtained as in Kauppi and Saikkonen (2008). In Section 5.1, we provide additional evidence using a dynamic probit model to show that our results are robust to the inclusion of a lagged dependent variable.

In order to select the best model, we make a search over different lag orders k and different combinations of the explanatory variables, where each lag is treated as a distinct predictor. We allow k to vary between 1 and 6, and we allow for combinations of up to five explanatory variables. In the earlier literature, it is custom to

[2] The probit model is also used by, among others, Dueker (1997), Estrella and Mishkin (1998), Chauvet and Potter (2005), Wright (2006), Kauppi and Saikkonen (2008), Nyberg (2010), and Ng (2012). Hamilton (2011) provides a recent survey. The results are robust to using a logit specification in place of the probit specification.