MACS 30200 Literature Review

Project: Forecasting U.S. recessions with a large number of predictors

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Over the last three decades, greater interest has been drawn to predicting recessions rather than only forecasting key quantities of economic activity. Two bodies of literature mainly contribute to this research field.

The first related literature is concentrated on identifying concrete recession predictors and constructing prediction models with a limited set of informative variables. Stock and Watson (1989, 1993) developed a recession prediction model in conjunction with the leading and coincident indicators. Their approach was to construct a vector autoregression (VAR) model and to derive the recession probabilities that it implies. One attractive feature of the model is that it empirically demonstrates the importance of financial variables such as interest rate spreads as leading indicators. This supports the view that financial variables provide significant information about whether an economy will be in a recession at a specific future date. More importantly, it incited a widespread interest in empirical research on the usefulness of financial variables for predicting the future state of an economy. For instance, Estrella and Mishkin (1998) focused on the out-of-sample performance of several financial variables as predictors of U.S. recessions. To avoid the relatively involved computation of recession probabilities implied by a high-dimensional vector autoregression (Stock & Watson, 1989, 1993), Estrella and Mishkin (1998) proposed to use the probit model, which directly predicts the binary dependent variable – whether the economy is in a recession or not.

One limitation of the linear relationship they defined within the probit model is only the values of selected variables at the predicted time are employed to forecast recessions. This implies that no information about past economic status is used to form predictions. Several papers discussed and demonstrated the importance of including the lagged values of the binary dependent variable within the probit function. Dueker (1997) and Moneta (2005) argued that since the error terms are generally auto-correlated, one underlying assumption of the probit model that the random shocks are independent and identically distributed normal variables is violated. They showed that incorporating lag terms of the binary dependent variable not only enhances the validity of the random sampling assumption on the error terms, but also improves the forecast power via including the information of past economic state.

More recently, Kauppi and Saikkonen (2008) extended previous dynamic probit models as follows in two innovative ways

$$\begin{aligned}\mathbb{E}_{t-1}(y_t) &= \mathbb{P}_{t-1}(y_t = 1) = \Phi(\pi_t) \\ &= \Phi\left(\sum_{j=1}^{p} \alpha_j \pi_{t-j} + \sum_{j=1}^{q} \delta_j y_{t-j} + x_{t-1}^{'}\beta + y_{t-d}x_{t-1}^{'}\gamma\right),\end{aligned} \quad (1)$$

where y_t and x_t represent the recession indicator and the interest rate spread respectively, π_t is determined by a considered specification, $\mathbb{E}_{t-1}(\cdot)$ and $\mathbb{P}_{t-1}(\cdot)$ denote as conditional expectation and conditional probability given the information set available at time $t-1$, and $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution. Apart from including lags of the binary dependent variable (y_{t-j}) and lagged values of the interest rate spread (x_{t-1}), the authors also included the conditional probability of the dependent variable based on lagged values of π_t. This enriches the dynamic structure of π_t. Moreover, the interaction term $y_{t-d}x_{t-1}^{'}$ represents the hypothesis that the effect of recession predictors would depend on a preceding state of the economy, effectively introducing a non-linear component. This model is the starting point for this project.

The second related literature, which has not been widely exploited, concerns using a large number of predictors to forecast recessions. Stock and Watson (1998) first introduced the idea of using a large set of predictors to forecast a macroeconomic time series variable rather than to predict an economic state of the business cycle. From the point of view of having a better in-sample results, it seems plausible to directly include a large number of predictor variables within a model. However, apart from the computational difficulty in including abundant explanatory variables, this is prone to resulting in a particularly poor out-of-sample performance due to the problem of overfitting. Hence, Stock and Watson (2002a, 2002b) developed a dynamic factor model. A handful of factors are extracted from all candidate predictors by principal component analysis (PCA), which approximately represent the most significant information containing in the large set of predictors. This innovation slacks the restriction that only a few series can be used in the previous forecasting process and the predictions based on a few factors perform well compared to several traditional benchmarks such as univariate autoregressive forecasts and vector autoregressive forecasts. Within the new proposed model, the authors only examined the linear predictive power of selected factors to an objective economic activity.

Consequently, one possible improvement in the model specification is to incorporate the predictors in a non-linear way. Bai and Ng (2008) suggested two feasible approaches to capture the non-linearity. Firstly, instead of having a linear relationship between the predictors and the factors, the method of quadratic principal components enriches the set of predictors by adding some or all cross-products of the predictors. Accordingly, extra non-linear characteristics of the predictors contribute to constructing the factors. These authors find that including all cross-products tends to result in overparameterization issues and suggest that extracting factors from only the original predictors and their squares is sufficient. Therefore, this project follows their recommendation to include nonlinearlity by extracting factors from predictors and their squares.

Although the common factor model mentioned above is usually applied to predict continuous real-valued macroeconomic variables (Stock & Watson, 2002a, 2002b; Bai & Ng, 2002, 2008), it is conceivable to expand its application to the forecasting framework of binary dependent variables such as recession indicators. Probit models are widely used to predict the probabilities of recessions (Dueker, 1997; Estrella & Mishkin, 1998; Chauvet & Potter, 2005; Moneta, 2005; Wright, 2006; Kauppi & Saikkonen, 2008), and most of the recent research related to recessions forecasting with common factors adopts the probit setup (for example, Chen et al., 2011; Christiansen et al., 2014).

Chen et al. (2011), who first combined the probit model with common factors to predict U.S. recessions, formed their probit-dynamic factor model only employing the current values of common factors as the regressors. They demonstrated that their model outperforms several existing models, including the Estrella-Mishkin (1998) model and the Wright (2006) model, according to both in-sample and out-of-sample criteria. The superior performance is mainly attributed to the fact that more essential information has been embedded in the common factors. Moreover, problems associated with structural changes and data revisions in individual explanatory variables are mitigated with the use of common factors. As a result, this project intends to predict recessions using common factors selected by PCA with a dynamic autoregressive probit model rather than the basic model used by Chen et al. (2011).

Apart from principal component regression, Bayesian shrinkage is regarded as another valid methodology to conduct predictions with a large panel of predictors. De Mol et al. (2008) proposed a scenario equivalent to a ridge regression to shrink the parameters of the regressors towards zero. Following their idea, Fornaro (2016) forecasted U.S. recessions with probit models estimated via Bayesian shrinkage. Compared to estimating latent factors by principal component analysis, Bayesian shrinkage improves the economic interpretation of the predictors. However, the computational expensiveness of using Bayesian methods, as well as their heavy reliance on somewhat arbitrary priors and the difficulty of incorporating nonlinearities in this setup, makes them less attractive for our purpose. Hence, this project adopts principal component analysis combined with the BIC as the primary method to deal with high-dimensional data. Besides, this project would like to use adaptive boosting (Adaboost), which is an effective tool for classification problems (Ng, 2014), to identify several most important predictors for predicting recessions. Including specific predictors will not only enhance the economic interpretation of the model but also provide a chance to compare the forecasting performance of models using common factors with models using the same number of selected predictors.

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