Applied Stochastic Models in Business and Industry

Discussion Paper

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Discussion on an approach for identifying and predicting economic recessions in real-time using time-frequency functional models

In this well-written and thorough manuscript, the authors creatively combine statistical methodologies to improve identification and prediction of recessions and expansions of the US economy. This is a timely topic, and one with concrete impact for financial analysts and market economists. The key statistical contribution is the introduction of the time-frequency spectrogram, which is based on the short-term Fourier transform, in collaboration with macroeconomic variables. Empirical orthogonal functions (EOFs) are used to reduce the dimensionality of the time-frequency spectrogram computed from two quarters of a daily index of NASDAQ returns preceding the time point. Variable selection of the EOFs as well as economic variables, for purposes of recession prediction, is conducted using Bayesian model averaging. The end result is a successful predictor and classifier of recessions.

Although, as noted by the authors, the paper is not designed to provide a full economic treatise on recessions and expansions, the authors do provide an excellent summary of key economic issues. Further, they provide a systematic study of the value of the factors considered in explaining and predicting recessions. I compliment the authors on their thorough study of this important topic.

A prudent observation by the authors is that the volatility in the daily NASDAQ index changes structure leading up to a recession. How to capture that changing structure will differ by analyst. Their approach is to take the daily NASDAQ index for two quarters and extract the EOFs of the spectrogram for each two quarter period. The EOFs form descriptor/predictor variables of recession and expansion periods. The selection of the EOFs providing the most information pertinent to the problem is made via Bayesian model averaging. The models that include the EOFs outperform equivalent models that exclude the EOFs, highlighting the efficacy of the spectrogram as a viable predictor variable for economic states. In fact, their classification percentages are exceptionally high, reaching a nowcast value of 0.95 for the area under the response operating curve (AUROC) for the pre-ultimate model, namely model 7, which includes both the economic covariates and the EOFs. Note that the AUROC for the nowcast based solely on the economic variables is higher than that of model 7; however, forecasting based on the simpler model does not hold up and model 7 prevails.

The authors gave strong consideration to the choice of the window width, in other words, the decision to focus on the previous two quarters of daily data. This choice leads to 120 observations from which to estimate each spectrum at each point in time. The smoothing then provided by the EOFs mitigates the temporal variation due to the large amount of sampling variability I expect would be present in a spectral estimate on the basis of 120 observations. The local nature of the signal is evidently diminished when a wider time window is used, as the authors point out that no descriptive signal is found when the spectrogram is based on a longer window.

The transition of the business cycle has been a standing question in the econometrics literature. As early as 1989, Hamilton introduced the idea of capturing non-stationary structure through regime switching models, which often have a Markov process managing the switch between regimes [1, 2]. The authors highlight the difficulty of ARCH–GARCH type modeling to extract the non-linear structure. I agree with their assessment and expect that a highly structured modeling approach, such as GARCH, would not perform near as well as the nimble non-parametric approach to the problem used by the authors. However, with signals as strong as what is indicated in the average spectrograms of Figure 1 of their paper, one would expect that reasonable GARCH approaches or more generally stochastic volatility models would also pick up this information, especially if subset models are considered. I direct the interested reader to a recent paper that addresses model-based filtering of stochastic volatility with the goal of understanding the underlying business cycle [3]. Further, I wonder if there is an opportunity here for parametric spectral estimation, a popular topic in the 1980s [4]. One cautionary note regarding modeling of the covariance includes estimation of the covariance itself, as outliers will have strong influence on any such estimator. For example, in intra-day data, the issues of trading frequency and liquidity become important as well as extreme outliers (see for example [5]). For general background on GARCH modeling for different regimes, or mixtures, see [6].

As another important direction to go in recession identification, the authors discuss the behavior of the yield curve in summarizing current monetary policy and encompassing economic signals. For readers interested in this topic, I direct them to a related macroeconomic paper examining yield curve estimation using wavelet time-frequency decomposition of interest [7]. For an improved strategy for estimation of the yield curve for corporate bonds, see [8].

Finally, an alternative spectral approach that would capture the same data features as the spectrogram would be a wavelet decomposition coupled with Bayesian selection of the key wavelet coefficients for purposes of explanation/classification and/or prediction, or *nowcasting* and *forecasting*. Selection of the wavelet coefficients is equivalent to the dimension reduction imposed by the EOFs. The wavelet coefficients selected will be a function of time just as the EOFs, providing the link to the identified recession/expansion periods. Further, it is unclear to me which strategy is most robust to extreme outliers or easier to compute. Certainly *wavelets*, with an explosion of similar methods over the past two decades, provide parsimonious representations of non-stationary time series with strong explanatory power. As the authors note in their text, the choice of basis function is not the focus of their paper. Further, an advantage to the Fourier basis function is direct interpretation in relation to the signal, in terms of short-term frequency components. However, it would be worthwhile to see the performance of the spectrogram coupled with the EOFs compared with that of a wavelet decomposition with selection of the wavelet coefficients with specific attention paid to improved forecasting in future work. For a recent exposition on wavelet-based classification, I point the reader to [9] and the references within. Also, I find the text *Wavelet Methods in Statistics with R* [10] to be a nice reference for the general topic.

The econometric, statistics and financial communities will continue to bring the best strategies forward for prediction and explanation of periods of recession and expansion. The resurgence of spectral methods to address problems in economics and finance is an important development. The authors are to be complimented on their contribution to this conversation.

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