**Setup of the Forecast Experiment**

1. Choose a target variable: either real GDP growth or inflation.
   1. GDP growth should be constructed as the log difference, log(GDPt)- log(GDPt-1), of the quarterly variable real GDP, where GDP is identified by the FRED mnemonic GDPC96, see <https://fred.stlouisfed.org/series/GDPC96>.
   2. Inflation should be constructed as the log difference, log(CPIt)- log(CPIt-1), of the monthly variable CPI (Consumer Price Index for All Urban Consumers: All Items), which is identified by the FRED mnemonic CPIAUCSL, see <https://fred.stlouisfed.org/series/CPIAUCSL>.
2. Choose an estimation method:
   1. Static factor model
   2. Dynamic factor model
   3. Boosting
   4. LASSO
   5. Elastic net
   6. Partial least squares
   7. Bayesian VAR
3. Try different specifications of your estimation model (e.g., vary the number of factors extracted, the tuning parameters in boosting, LASSO, elastic net and partial least squares, or the prior in Bayesian approaches).
4. Take a huge data set:
   1. A set of 146 monthly variables is provided in the Excel file “SW\_Updated.xls” which also contains the series of quarterly GDP.
   2. If you like you are invited to add interesting variables that you may find, e.g., on the websites of FRED (<https://fred.stlouisfed.org/>), the BLS (<https://www.bls.gov/data/>) or the Federal Reserve Board (<https://www.federalreserve.gov/data.htm>).
5. Fix the forecast horizon:
   1. GDP growth: 1, 2, 4, and 8 quarters ahead
   2. Inflation: 1, 3, 6, 12 and 24 months ahead
6. Think about the data frequency:
   1. GDP growth is available only quarterly while the indicators are monthly. One way to deal with this problem is to aggregate all indicators to the quarterly frequency. Another one is to create three quarterly variables out of one monthly variable x: x1 is the first-month-of-a-quarter variable, x2 is the second-month-of-a-quarter variable, and x3 is the third-month-of-a-quarter variable. An even more advance method is to use mixed frequency methods such as MIDAS (which stands for mixed data sampling and not for an ancient king) but this might be too advanced for this course and not really necessary given that you condense or select information anyway using one of the methods above.
   2. Inflation and the indicators are monthly so no problem exists.
7. Take revisions into account. Typically, macroeconomic variables are revised over time. Hence, a forecaster at, say the end of 2001Q1 uses a different GDP value for 2000Q4 than a researcher today. However, to simplify the analysis in this seminar, we neglect any revision and use the data set as it is.
8. Take publication lags into account. Most variables are published with a time lag which sometimes may be considerable. Again, to make life simple we neglect this problem and assume that at the end of one month all realizations of that month are known and can be used to forecast future months. Similarly, we assume that at the end of one quarter all realizations of that quarter are known and can be used to forecast future quarters.
9. Choose the evaluation period:
   1. GDP growth: for each forecast horizon, generate forecasts for the period 2000Q1 to 2016Q4. Hence, for an h-step forecast, the first estimation sample ends in period 2000Q1-h.
   2. Inflation: for each forecast horizon, generate forecasts for the period 2000M1 to 2016M12. Hence, for an h-step forecast, the first estimation sample ends in period 2000M1-h.
   3. In both cases, you may also consider a subsample if you think this is interesting. For example, you may want to exclude the Great Recession to see whether this episode dominates the evaluation results.
10. Perform an out-of-sample forecast experiment. 
11. Use a simple AR(1) as a benchmark.
12. Compare forecast accuracy of your specifications in terms of the squared forecast error: mean squared forecast error, mean squared forecast error relative to the benchmark (Theil’s U), and a test of equal forecast accuracy against the benchmark. If you have non-nested forecasts (meaning that one forecasting model is **not** just a restricted version of the other one) use the Diebold-Mariano test. If you have nested forecasts (meaning that one forecasting model **is** a restricted version of the other one), use the “MSPE-adjusted” test of Clark and West (2007, section 2). In both cases, recall that h-step forecast errors are expected to be autocorrelated of order h-1. Therefore, for h>1 use Newey-West standard errors to compute the test statistic. (We upload Matlab functions that compute the Diebold-Mariano and the Clark-West test statistics.)