Technical Description of Energy Price BVAR

To estimate the impact of the energy price shocks occurring in the second half of this year on (real) gross domestic product (GDP), consumption, and business fixed investment, we use a Bayesian vector autoregression model (BVAR). The quarterly BVAR has five lags and is estimated over the 1987Q3 to 2014Q3 sample period. The variables are log levels of the following nine variables:

1.) Real consumption: Durable goods
2.) Real consumption: Nondurable goods and services
3.) Real business fixed investment: Mining and oilfield equipment and structures
4.) Real business fixed investment excluding mining and oil field equipment and structures
5.) Real GDP excluding consumption and business fixed investment
6.) Core personal consumption expenditure (PCE) prices
7.) Real broad trade-weighted exchange value of the U.S. dollar
8.) Producer price index (PPI): PPI: Processed Fuels and Lubricants (SA, 1982 = 100)
9.) PCE: Energy Goods & Services: Chain Price Index

Following Edelstian and Kilian (2007), "PPI: Processed Fuels and Lubricants (SA, 1982 = 100)," from the U.S. Bureau of Labor Statistics, is intended to capture the cost of energy to firms. The broad dollar index is from the Federal Reserve Board, and the remaining seven variables come from the U.S. Bureau of Economic Analysis. The authors constructed variables 2 and 3 using Fisher chain weighting, and variables 4 and 5 are constructed by Fisher subtraction. To implement the BVAR, we use the algorithm described in Banbura, Giannone, and Reichlin (2008). This approach involves augmenting the data of an ordinary VAR with so-called "dummy observations." The hyperparameters used to construct the dummy observations are described in Banbura, Giannone, and Reichlin (2008) as well.

Briefly, each variable in the BVAR is associated with a parameter $\delta_i = 1$ that reflects the prior belief that the variable is a random walk. The hyperparameter λ controls the overall tightness of the prior; setting $\lambda = 0$ means the data are ignored and the estimation only uses prior information. Setting $\lambda = \infty$ means prior information is not used at all and the BVAR is simply a VAR estimated by OLS. For $0 < \lambda < \infty$, small values of λ put a heavy weight on the prior information, and large values of λ put little weight on the prior information. We follow Banbura, Giannone, and Reichlin (2008) in choosing λ so that the one step ahead forecast error for three key variables in the BVAR is roughly the same as it would be with a 3-variable VAR with three key variables only. These are variables 2 through 4 in the above list, and in our implementation $\lambda = 0.2$. Finally, we include the prior on the sum of coefficients setting $\tau = \lambda$.

The authors' "nowcasts" estimate the 2014Q4 values of the variables. The BVAR can be written as

$$(\mathbf{1})\ \boldsymbol{y}_t = \boldsymbol{\alpha} + \boldsymbol{B}_1\boldsymbol{y}_{t-1} + \boldsymbol{B}_2\boldsymbol{y}_{t-2} + \cdots + \boldsymbol{B}_5\boldsymbol{y}_{t-5} + \boldsymbol{u}_t$$

where $\boldsymbol{\Omega}_u$ is the covariance matrix of the reduced form shocks $\boldsymbol{u}_t$. We use the Cholesky decomposition to factor $\boldsymbol{\Omega}_u = \boldsymbol{L}\boldsymbol{L}'$ where $\boldsymbol{L}$ is a 9x9 lower triangular matrix (i.e., entries above the main diagonal are 0) and write

$$(\mathbf{2})\ \boldsymbol{u}_t = \boldsymbol{L}\boldsymbol{\epsilon}_t$$

where $\boldsymbol{\epsilon}_t$ is a vector of structural economic shocks with a multivariate standard normal distribution. The 2014Q3 and 2014Q4 values of the structural shocks can be solved from

$$(\mathbf{3})\ \boldsymbol{\epsilon}_t = \boldsymbol{L}^{-\mathbf{1}}\boldsymbol{u}_t$$

All of this is described in more detail in Hamilton (1994). This identification scheme requires us to take a particular stand on the order in which we enter the variables in the BVAR. We always enter the energy price variables—numbers 8 and 9 in the above list—adjacent to each other with “PPI: Processed Fuels and Lubricants (SA, 1982=100)” ordered first and “PCE: Energy Goods & Services: Chain Price Index” ordered second. Using this “block” ordering of the energy price variables, we average over the 8! = 40,320 possible orderings of the variables. For each of these orderings, we can identify the 2014Q3 and 2014Q4 values of the energy price shocks in equation (3) and zero them out in the “baseline” simulation. The “alternative” simulation does not replace these values with 0. In the simulations, real business fixed investment, real GDP, and real consumption are derived using a Tornqvist index with the 2014Q3 expenditure shares.

References:

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