Box 2. Indentifying Demand and Supply Shocks

First, we consider the presence of trends in our price and quantity measures of global liquidity. According to the (two standard) augmented Dickey-Fuller (ADF) and Phillips-Perron unit root tests, the quantity indicators of global liquidity (both expressed as a ratio to GDP and in U.S. dollars) contain a unit root, Thus, one can decompose the quantity indicators into a trend and cycle component. The trend growth of Noncore and core liabilities as a ratio to GDP is 1 percentage point and half a point per quarter, respectively. Deviations from trend are persistent. Thus, by assuming a linear trend, all stochastic variation in the quantity series is interpreted as persistent supply and demand shocks.

Next, a vector auto-regression (VAR) model is used to identify the demand and supply shocks to global liquidity using the sign restriction approach. After regressing the de-trended quantity and price indicators of global liquidity on their lagged values using quarterly data from 1999Q1 to 2011Q1, it is possible to identify supply and demand shocks using sign restrictions. Initially, one can consider an unrestricted VAR model:

$$x_t = c + B(L)x_{t-1} + \varepsilon_t, \tag{1}$$

where x_{t} is a vector containing both the price and quantity measures of global liquidity at time t, B is the matrix polynomial in lags with an order p (based on Bayesian Information Criterion) , and ε_{t} is a vector of reduced form residuals assumed to be normally distributed with mean zero and covariance matrix Ω. Using the Cholesky decomposition, it is possible to convert equation (1) into a structural model with a diagonal covariance matrix.

$$(PQ)^{-1}x_t = (PQ)^{-1}c + (PQ)^{-1}B(L)x_{t-1} + u_t, \tag{2}$$

where P is matrix such that $\mathrm{PP}' = \mathbb{b}$, Q is an orthonormal matrix,[5] u_t are structural residuals with identity matrix as the covariance matrix.

Because different rotations of the matrix P (or different values of Q) yield observationally the same values of the likelihood functions, it is possible to choose the specification whose impulse responses match the sign restrictions. Also, to limit the choice of models to a particular range of magnate impulse responses, this paper uses the "median targeting" approach, which picks the median impulse response among a large number of iterations.[1]

Having identified individual supply and demand shocks, one can use a World historical decomposition procedure to identify cumulative contributions of supply and demand shocks (see, for example, Kilian, 2009, for decomposing oil demand and supply factors). Thus, after choosing a particular model which matches the sign restrictions, historical decomposition rewrites (2) as:

$$y_t = a + \Psi_1\epsilon_{\mathrm{t}}^{\mathrm{d}} + \cdots + \Psi_\infty\epsilon_{\mathrm{t}-\infty}^{\mathrm{d}} + \Pi_1\epsilon_{\mathrm{t}}^{\mathrm{s}} + \cdots + \Pi_\infty\epsilon_{\mathrm{t}-\infty}^{\mathrm{s}} , \tag{3}$$

with y_t is decomposed into current and past structural demand ($\epsilon_{\mathrm{t}}^{\mathrm{d}}$) and supply ($\epsilon_{\mathrm{t}}^{\mathrm{s}}$) shocks.

[1]The small sample size limits the estimation to a time invariant VAR. The minimum number of models is between 3,000 or the number such that the difference between the median responses of two sets of models is reasonably small (see also Fry and Pagan (2010) for details).