Identifying Aggregate Liquidity Shocks with Monetary Policy Shocks: An Application using UK Data

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Motivation & Related Literature

How to capture unconventional monetary policies in a VAR model using data before 2009?

- Liquidity

  Kiyotaki and Moore (2012); Shi (2015); Baumeister et al. (2008); Adalid and Detken (2007)

- Monetary Policy and Sign Restrictions

  Canova and De Nicoló (2002); Uhlig (2005)

- Uconventional Monetary Policies

  Gambacorta et al. (2014); Weale and Wieladek (2016)

Contribution & Key Findings

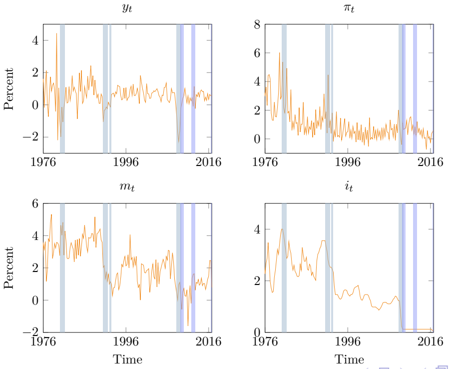
We propose an aggregate liquidity shock in conjunction with a traditional monetary policy shock in a structural VAR model.

Findings:

- Substantial evidence in favour of a time-varying transmission of aggregate liquidity shocks
- Statistically significant differences in the contribution of aggregate liquidity shocks to macroeconomic variation at a business cycle frequency
- Aggregate liquidity shocks contribute 32% and 47% to the variance of GDP and inflation at business cycle frequencies following the 2008 recession, respectively
- During the Great Recession, the economic significance of these shocks for GDP and inflation forecast error variances are 14 and 13 times greater relative to shocks identified using a Cholesky decomposition

Data

Our estimated model uses UK data from 1976Q1-2016Q4 on: quarterly real GDP growth, y_t; consumer price inflation, π_t; our construction of a break adjusted M4/M4ex (which excludes other intermediate financial corporations) series, m_t; and the Bank of England Bank rate, i_t.



The Model I

We work with the following TVP–VAR model with 2 lags and 4 variables:

$$Y_t = \beta_{0,t} + \beta_{1,t} Y_{t-1} + \beta_{2,t} Y_{t-2} + \epsilon_t \equiv X_t^{'} \theta_t + \epsilon_t$$

the VAR's time–varying parameters are collected in θ_t and evolve as

$$p(\theta_t | \theta_{t-1}, Q) = I(\theta_t) f(\theta_t | \theta_{t-1}, Q)$$

$$\theta_t = \theta_{t-1} + \nu_t$$

The innovations $\epsilon_t \backsim N(0, \Omega_t)$. Ω_t is the time–varying covariance matrix which we factor as

$$Var(\epsilon_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})^{'}$$

The Model II

Collecting the non-unit and non-zero elements in A_t in the vector $\alpha_t = [\alpha_{2,1,t}, ..., \alpha_{4,3,t}]'$ and the diagonal elements of H_t in $h_t = [h_{1,t}, ..., h_{4,t}]'$, they evolve as

$$\begin{aligned} \alpha_t &= \alpha_{t-1} + \zeta_t \\ \ln h_t &= \ln h_{t-1} + \eta_t \end{aligned}$$

The innovations in the model are jointly Normal

$$\begin{bmatrix} u_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix} \backsim N(0, V), \quad V = \begin{bmatrix} I_M & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}$$

where u_t is such that, $\epsilon_t \equiv A_t^{-1} H_t^{\frac{1}{2}} u_t$; Q, S, W are positive definite matrices.

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Our Proposed Identification Scheme I

Table: Identification Restrictions

Shock:	Aggregate Liquidity, u_t^L	Monetary Policy, u_t^{MP}
Variable		
y_t	$\geq$	$\leq$
π_t	x	$\leq$
m_t	$\geq$	$\leq$
i_t	0	$\geq$

Our Proposed Identification Scheme II

Let

$$\Omega_t = P_t D_t P_t'$$

be eigenvalue-eigenvector decomposition of Ω_t.
Draw an $M \times M$ matrix K from the $N(0,1)$ distribution and compute the QR decomposition of K. The time-varying structural impact matrix is

$$A_{0,t} = P_t D_t^{\frac{1}{2}} Q'$$

Our Proposed Identification Scheme III

To impose the single zero restriction we compute a deterministic rotation of $A_{0,t}$ we define the rotation matrix, RM as

$$RM = \begin{bmatrix} I_2 & 0_{2\times 2} \\ 0_{2\times 2} & \begin{bmatrix} c & -s \\ s & c \end{bmatrix} \end{bmatrix}$$

where $RM \cdot RM' = I_M$ and

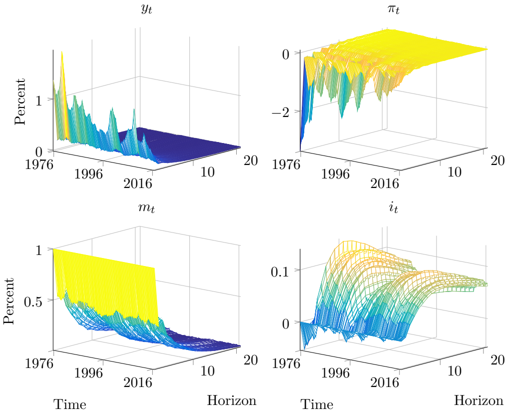
$$c = \frac{A_{0,t}(4,4)}{\sqrt{A_{0,t}(4,3)^2 + A_{0,t}(4,4)^2}}, \; s = -\frac{A_{0,t}(4,3)}{\sqrt{A_{0,t}(4,3)^2 + A_{0,t}(4,4)^2}}$$

We obtain a new impact matrix, $\bar{A}_{0,t} = A_{0,t} \cdot RM$ with a zero in the (4,3) position.

Prior Information

- To calibrate the model, we use the OLS estimates from a constant parameter VAR using the first 20 years of data from 1955Q4-1975Q4
- Our prior specifications are similar to that of Baumeister and Peersman (2013)
- We allow for 100,000 runs of the Markov Chain Monte Carlo Simulation burning the first 50,000
- Of the remaining 50,000 we sample every 10^{th} draw to reduce autocorrelation

The Impact of Aggregate Liquidity Shocks



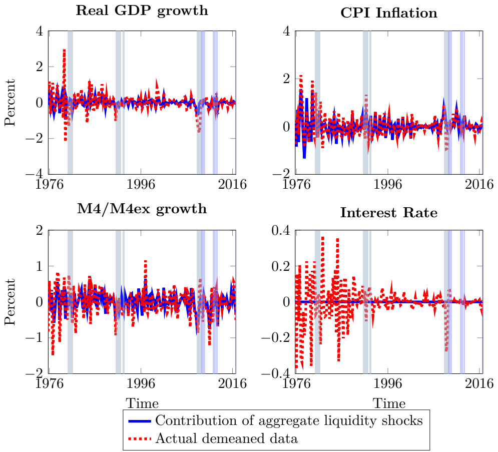
Historical Decomposition of Aggregate Liquidity Shocks

To interpret the figure on the next slide:

- The dashed line reports the actual time series relative to its fitted value
- The solid line shows the cumulative effects of aggregate liquidity shocks on the evolution of each variable, while turning off all other shocks
- Therefore, the figure shows how the variable in question would have evolved if **only** aggregate liquidity shocks occurred (therefore aggregate liquidity shocks have zero contribution toward movements in the interest rate)

The difference between the dashed and solid line represents the contribution all other shocks.

Historical Contribution of Aggregate Liquidity Shocks

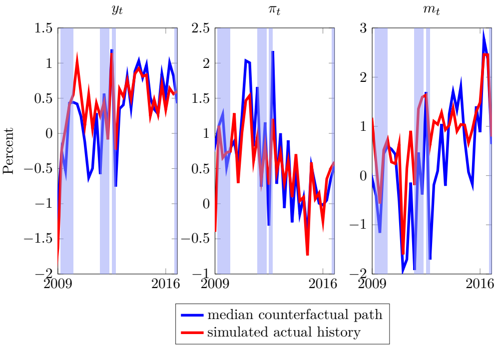


Does our Identified Shock Capture Quantitative Easing?

- Had policymakers chosen not to implement successive rounds of Quantitative Easing, the volatility of aggregate liquidity shocks would have been less turbulent
- Therefore to determine whether our proposed shock captures unconventional monetary policies we report results from a counterfactual simulation changing the volatility of these shocks following the Great Recession
- We set the standard deviation of structural liquidity shocks from 2009Q1-2016Q4 to the average volatility of these shocks from 1976Q1-2008Q4

Does our Identified Shock Capture Quantitative Easing?

- The blue line represents the median counterfactual path had no asset purchase facilities been implemented
- The red line is the simulated actual history implied by our model



Business Cycle Frequency Variance Decomposition

The unconditional spectral density of variable $x = \{y_t,\ \pi_t,\ i_t,\ m_t\}$ at frequency ω is given by

$$f_{x,t|T}(\omega) = s_x(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\frac{\bar{A}_{0,t|T}(\bar{A}_{0,t|T})'}{2\pi}\left[(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\right]' s_x'$$

The conditional spectral density of variable $x = \{y_t,\ \pi_t,\ i_t,\ m_t\}$ is

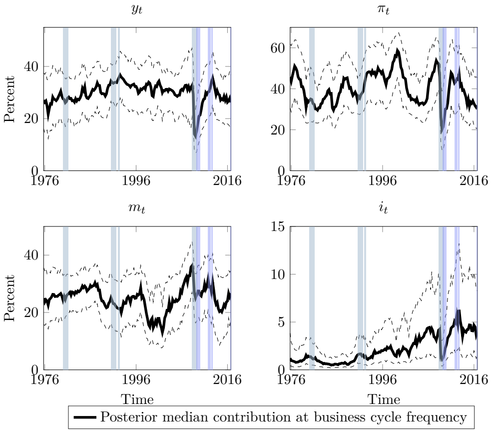
$$\bar{f}_{x,t|T}(\omega) = s_x(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\frac{\underline{A}_{0,t|T}(\underline{A}_{0,t|T})'}{2\pi}\left[(I_4 - \tilde{\beta}_{t|T}e^{-i\omega})^{-1}\right]' s_x'$$

where $\underline{A}_{0,t|T}(\underline{A}_{0,t|T})'$ which shuts off all structural shocks except for the one of interest. Therefore the contribution of identified structural shocks is given by the ratio

$$\frac{\bar{f}_{x,t|T}(\omega)}{f_{x,t|T}(\omega)}$$

Business Cycle Frequency Variance Decomposition

Following Hamilton (1994) we define business cycle frequency as 10 quarters



Robustness

Our robustness analysis reveals:

- Aggregate liquidity shocks retrieved from a Cholesky decomposition are not well defined and yield little economic significance
- Our contemporaneous zero restriction on the interest rate is plausible (from historical decompositions using a Cholesky decomposition thereby allowing for liquidity shocks to affect i_t on impact)
- There are no statistically significant differences in our results when replacing M4/M4ex with Divisia money

Conclusions

- Real GDP and inflation become more sensitive to aggregate liquidity shocks during recessions
- These shocks hold historical importance by contributing significantly to macroeconomic movements, and variance
- Counterfactual simulations indicate our shocks capture unconventional monetary policies, our estimates imply the recovery in GDP growth following QE1 would have been more gradual
- At the onset of the Great Recession, aggregate liquidity shocks explain 32% and 47% of the variance in GDP and inflation at business cycle frequencies respectively

Extensions of our Work on Liquidity Shocks

In a 'sister' paper *On Stock Market Illiquidity Shocks and UK Macroeconomic Dynamics*, we examine the impact of illiquidity shocks in a time-varying parameter VAR model accounting for the financial sector by including proxies for stock market liquidity. Our results show:

- Illiquidity shocks cause real GDP growth and inflation to contract by 2% and 2.6% in 2008Q4
- From 2010Q4–2016Q4, the percent of forecast error variance explained by these shocks for GDP growth and inflation variability are 22% and 27%, respectively
- There are statistically significant differences in FEVDs indicating that the importance of illiquidity shocks move with the business cycle

Monetary Policy Shocks under our Identification Scheme