Identifying Aggregate Demand and Supply Shocks Using Sign Restrictions and Higher-order Moments

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Contribution 1/3

- Disentangling aggregate demand (AD) and aggregate supply (AS) shocks is a key question in macroeconomics:
  - Economic impact can be different (e.g., Blanchard and Quah, 1989)
  - Policy responses often different
- However, practically, the identification is complex with many assumptions (e.g., Canova and Paustian, 2011; Furlanetto, Ravazzolo, and Sarferaz, 2019)
- **This paper**: a methodology with minimal theoretical assumptions relying only on unconditional higher-order moments in GDP growth and inflation data

Contribution 2/3

- **This paper**: distinguishing between aggregate demand (AD) and aggregate supply (AS) shocks uncertainty

Contribution 3/3

- Recent interest in non-Gaussian uncertainty (e.g., Adrian, Boyarchenko, and Giannone, 2019; Fernandez-Villaverde and Guerron-Quintana, 2020)
- **This paper**: flexible econometric framework for multivariate distribution of macro data
    - Formally outperforms other non-Gaussian models
    - Time-varying closed-form second/higher-order moments
    - Time-varying level and uncertainty/higher order moment shock correlation (Gorodnichenko and Ng, 2017; Carriero et al., 2018; Alessandri and Mumtaz, 2019)

Aggregate Supply and Demand Shocks

- Consider GDP growth and inflation shocks:
  - $g_{t+1} = E_t[g_{t+1}] + \epsilon^g_{t+1}$
  - $\pi_{t+1} = E_t[\pi_{t+1}] + \epsilon^\pi_{t+1}$
- Model them as functions of AD (u^d_t)/AS (u^s_t) shocks (Blanchard, 1989):

$$\epsilon^g_{t+1} = \underbrace{\sigma^d_g}_{>0} u^d_{t+1} + \underbrace{\sigma^s_g}_{>0} u^s_{t+1},$$

$$\epsilon^\pi_{t+1} = \underbrace{\sigma^d_\pi}_{>0} u^d_{t+1} - \underbrace{\sigma^s_\pi}_{>0} u^s_{t+1},$$

$$Cov(u^d_{t+1}, u^s_{t+1}) = 0, Var(u^d_{t+1}) = Var(u^s_{t+1}) = 1.$$

Identification

- "Demand" and "supply" shocks are not identified in a Gaussian framework (3 unconditional moments: 2 variances+covariance, but 4 σ coefficients to estimate)$\Rightarrow$ **use unconditional higher-order moments**

- For example, identification via matching co-skewness moments:

$$E[u_t^g(u_t^\pi)^2] = \sigma_g^d(\sigma_\pi^d)^2 E[(u_t^d)^3] + \sigma_g^s(\sigma_\pi^s)^2 E[(u_t^s)^3],$$
$$E[(u_t^g)^2 u_t^\pi] = (\sigma_g^d)^2\sigma_\pi^d E[(u_t^d)^3] - (\sigma_g^s)^2\sigma_\pi^s E[(u_t^s)^3].$$

- For example, suppose $E[(u_t^s)^3] \approx 0$ and $E[(u_t^d)^3] < 0$:
  - $E[u_t^g(u_t^\pi)^2] \approx \sigma_g^d(\sigma_\pi^d)^2 \underbrace{E[(u_t^d)^3]}_{<0}$
  - $E[(u_t^g)^2 u_t^\pi] \approx (\sigma_g^d)^2\sigma_\pi^d \underbrace{E[(u_t^d)^3]}_{<0}$
  - co-skewness moments admit identification of σ_π^d and σ_g^d
  - if $E[u_t^g(u_t^\pi)^2] < E[(u_t^g)^2 u_t^\pi] \Rightarrow \sigma_\pi^d > \sigma_g^d$

Modeling demand and supply shocks

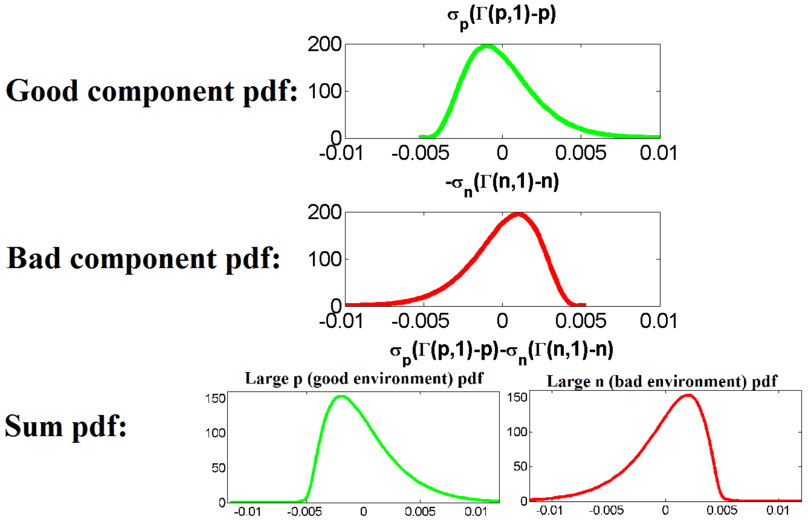
- Demand and supply shocks modeled using Bad Environment-Good Environment (BEGE) structure (Bekaert and Engstrom, 2017): component models of two 0-mean shocks

$$\left.\begin{aligned} u^d_{t+1} &= \sigma^d_p \omega^d_{p,t+1} - \sigma^d_n \omega^d_{n,t+1}, \\ u^s_{t+1} &= \sigma^s_p \omega^s_{p,t+1} - \sigma^s_n \omega^s_{n,t+1}, \end{aligned}\right\} \begin{aligned} &\omega_{p,t+1} \text{ - good environment shock} \\ &\omega_{n,t+1} \text{- bad environment shock} \end{aligned}$$

- Shocks follow demeaned gamma distributions:

$$\left.\begin{aligned} \omega^d_{p,t+1} &\sim \Gamma(p^d_t, 1) - p^d_t, \\ \omega^d_{n,t+1} &\sim \Gamma(n^d_t, 1) - n^d_t, \\ \omega^s_{p,t+1} &\sim \Gamma(p^s_t, 1) - p^s_t, \\ \omega^s_{n,t+1} &\sim \Gamma(n^s_t, 1) - n^s_t. \end{aligned}\right\} \Gamma(x, y) - \text{gamma distribution with shape parameter x and scale parameter y}$$

Bad Environment-Good Environment Probability Density Function



Time-varying variances

- AR(1) process for shape parameters of demeaned gamma distributions:

$$p^d_{t+1} = \bar{p}^d + \rho^d_p(p^d_t - \bar{p}^d) + \underbrace{\sigma^d_{pp}\omega^d_{p,t+1}}_{\text{level shock}} + \underbrace{\sigma^{dd}_{pp}\nu_{p,t+1}}_{\text{pure variance shock}}$$

- Similar processes for n^d_{t+1}, p^s_{t+1}, n^s_{t+1}
- p^d_t / n^d_t = good (positively skewed)/bad (negatively skewed) demand variances
- p^s_t / n^s_t = good (positively skewed)/bad (negatively skewed) supply variances
- Flexible time-varying correlation between level and variance shocks: good/bad variance positively/negatively correlated with level shocks

Bad Environment-Good Environment Structure Properties

- Flexible: e.g., Gaussian and rare disaster distributions are special cases
- Closed-form expressions for second and higher-order moments
- Outperforms other non-Gaussian models (e.g., regime-switching models)

Data and Estimation

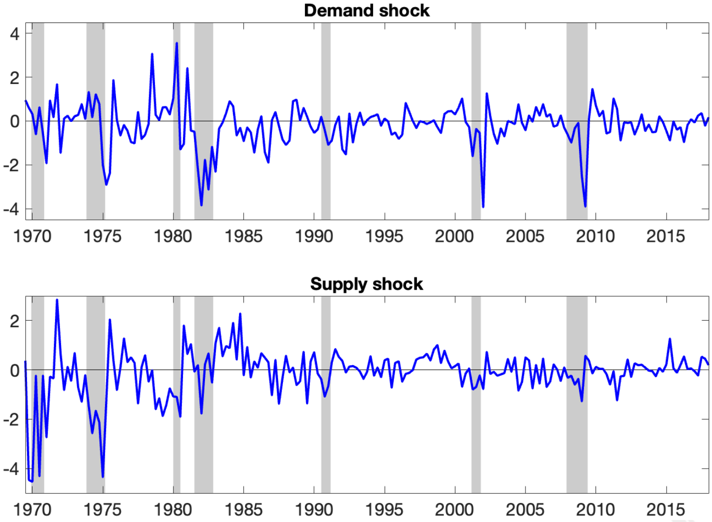
- US quarterly data 1968Q4-2019Q2
- 3 step estimation:
    - Shocks to output growth and inflation: real-time data from Survey of Professional Forecasters
    - Demand and supply shocks: invert from output growth and inflation shocks after estimating "structural" loadings via GMM using higher-order moments **(3^{rd} and 4^{th} order moments are jointly highly significant and GMM fits them well)**
    - Conditional volatility/higher-order moment dynamics $(p_t^d, n_t^d, p_t^s, n_t^s)$: maximum likelihood

Loadings of GDP Growth and Inflation Shocks onto Supply and Demand Shocks

	u_t^π	u_t^g
u_t^s	-0.4829	1.1802
	(0.0566)	(0.1129)
u_t^d	0.5141	0.6035
	(0.0685)	(0.1064)

standard errors in parentheses

AS/AD Shocks

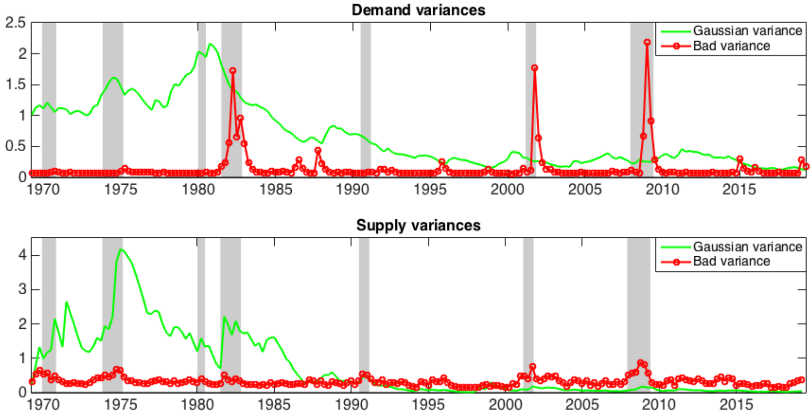


NBER recessions shaded

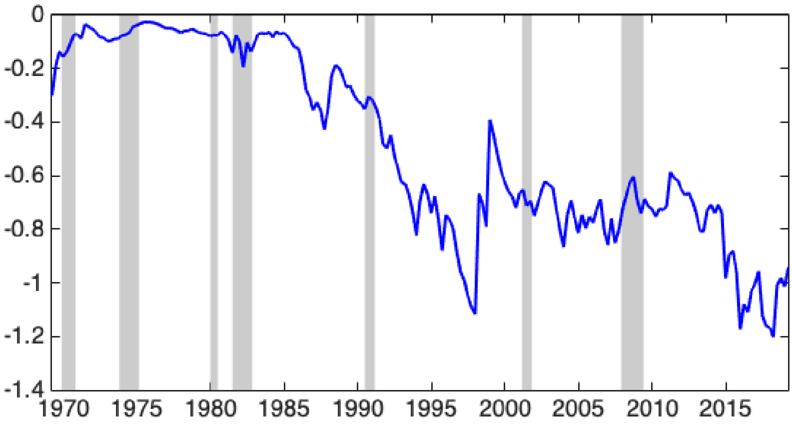
AS/AD shock distributions

- Bad environment/good environment model selection based on Akaike information criterion
- AS:
  - Good component: Gaussian; level and variance shocks are independent
  - Bad component: gamma with occasional medium-sized left-tail realizations; level and variance shocks are perfectly correlated
- AD:
  - Good component: Gaussian; level and variance shocks are perfectly correlated
  - Bad component: rare-disaster type; level and variance shocks are perfectly correlated

AS/AD Variances

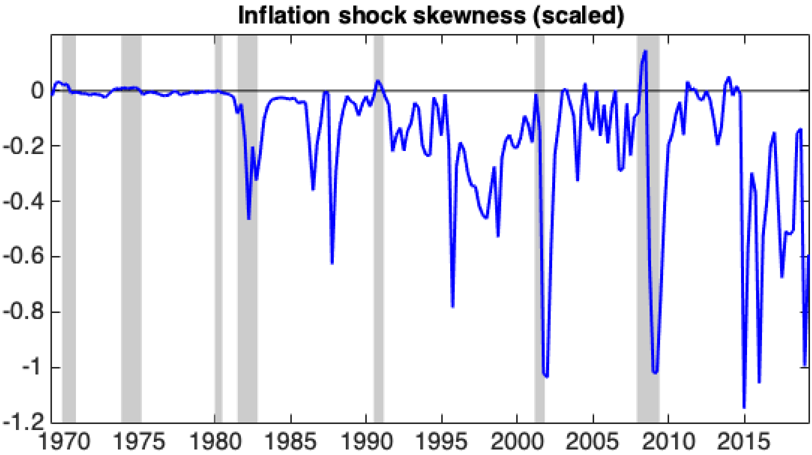


Real GDP Growth Skewness (Scaled)

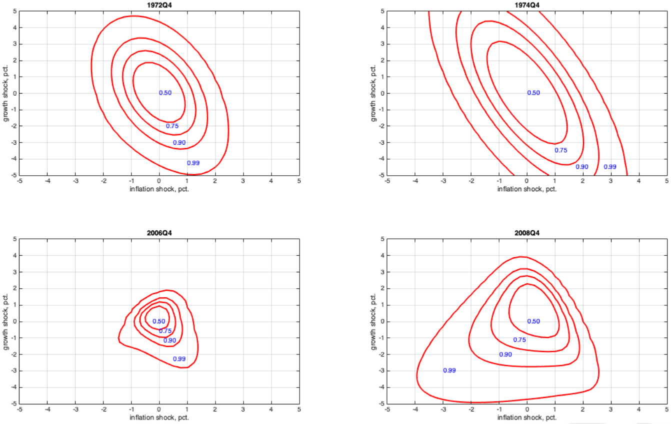


Consistent with Jensen et al. (2021)

Inflation Skewness (Scaled)

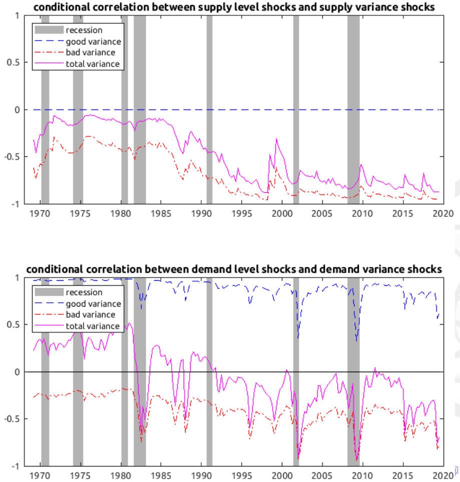


Conditional Contour Plots of Joint Real GDP Growth - Inflation Distribution



Numbers correspond to percentiles

Conditional Correlation between Level and Variance Shocks



Conclusions

- A novel method to identify AD and AS shocks with minimal theoretical assumptions using higher-order moments of macro data
- New non-Gaussian dynamic model for joint distribution of real GDP growth and inflation
- Relative importance of non-Gaussian features in macro data increasing over time due to decreasing Gaussian volatility