A New Decomposition of U.S. Recessions and Crises into Aggregate Supply and Demand Components

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Motivation

- Distinguishing between aggregate demand (AD) and aggregate supply (AS) shocks is central topic in empirical macro (e.g., Shapiro and Watson, 1988):
  - Economic impact of AD/AS shocks can be different (e.g., Blanchard and Quah, 1989)
  - Policy responses to AD/AS shocks often different

Contribution

- Most empirical methods distinguishing aggregate demand/aggregate supply shocks suffer from at least one of the following requirements:
  - Many/complex theoretical assumptions
  - Computationally heavy
  - Require (often proprietary) micro data
- We propose method based on non-Gaussian features of macroeconomic data, which requires:
  - Minimal theoretical assumptions (just 2 sign restrictions)
  - Computationally light (generalized method of moments with small number of parameters)
  - Just 2 macro time series (GDP growth and inflation)

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 Gaussian framework $\Rightarrow$ use unconditional higher order moments

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

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

- Imagine: $E[(u_t^s)^3] \approx 0$ and $E[(u_t^d)^3] < 0$:
  - co-skewness moments admit identification of σ_π^d and σ_g^d
  - if $E[\epsilon_t^g(\epsilon_t^\pi)^2] < E[(\epsilon_t^g)^2\epsilon_t^\pi] \Rightarrow \sigma_\pi^d > \sigma_g^d$

Modeling conditional means

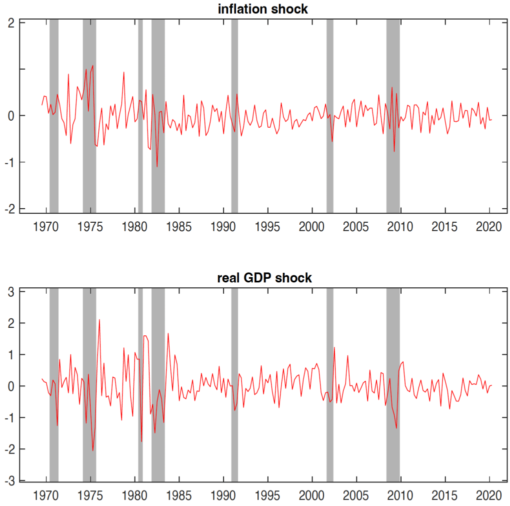
- Real-time quarterly GDP growth (g_t) and inflation (π_t) data 1969Q2-2019Q4/2024Q4
- VAR to model conditional mean
- Akaike Information Criterion to pick optimal variables/number of lags

Optimal VAR to Model Conditional Mean 1969Q2-2019Q4

- 1 lag
- Past GDP growth and inflation realizations and Survey of Professional Forecasters forecasts are optimal predictors

	π_{t-1}	g_{t-1}	$SPF_{t-1}(\pi_t)$	$SPF_{t-1}(g_t)$
π_t	0.4102	0.0287	0.6128	-0.0123
Std. Error	(0.1168)	(0.0518)	(0.1202)	(0.0733)
g_t	-0.3419	0.1513	0.2869	0.8192
Std. Error	(0.2103)	(0.0924)	(0.2060)	(0.2304)
$SPF_t(\pi_{t+1})$	0.2355	0.0579	0.7285	-0.0030
Std. Error	(0.0432)	(0.0165)	(0.0425)	(0.0222)
$SPF_t(g_{t+1})$	-0.1977	-0.0558	0.1745	0.8223
Std. Error	(0.0882)	(0.0503)	(0.1150)	(0.0891)

Inflation and GDP Growth Shocks 1969Q2-2019Q4 (Annualized %)



GDP Growth and Inflation Shock Higher-Order Moments: 1969Q2-2019Q4

Panel A: Scaled (co-)skewness

	skew(π,π,π)	skew(g,g,g)	skew(π,π,g)	skew(π,g,g)
Estimate	0.2944	0.1016	-0.3924	0.2313
(Std. Error)	(0.2578)	(0.2792)	(0.1468)	(0.0953)

Panel B: Scaled excess (co-)kurtosis

	xkurt(π,π,π,π)	xkurt(g,g,g,g)	xkurt(π,π,g,g)	xkurt(π,π,π,g)
Estimate	1.4432	1.7753	1.2106	-0.3335
(Std. Error)	(0.5771)	(0.7038)	(0.3576)	(0.6458)
	xkurt(π,g,g,g)			
Estimate	-0.6626			
(Std. Error)	(0.3074)			

Panel C: Jarque-Bera Tests (p-values)

	p-value(π)	p-value(g)	p-value(π,g)
	< 0.001	< 0.001	< 0.001

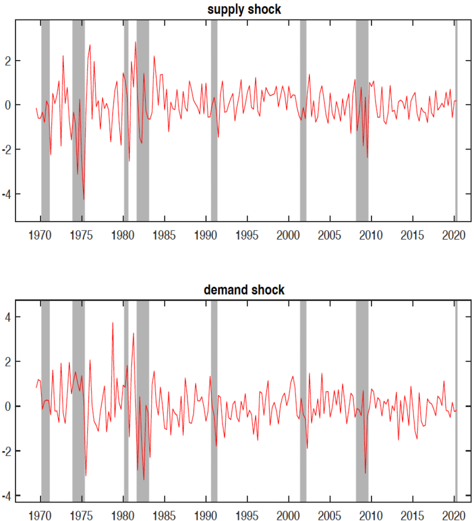
Loadings of GDP Growth and Inflation Shocks onto Supply and Demand Shocks

- Estimating loadings by fitting second and higher order GDP growth and inflation shock moments: GMM fit moments nicely with *J*-test p-value of 59%

	Inflation	GDP growth
Aggregate supply	-0.2423	0.4991
	(0.0660)	(0.0852)
Aggregate demand	0.2302	0.3625
	(0.0366)	(0.0851)

standard errors in parentheses

Aggregate Demand and Aggregate Supply Shocks 1969Q2-2019Q4 (Annualized %)



Decomposing of Recession Shocks 1969:Q2-2019:Q4

NBER Recession	Demand Component (%)	Supply Component (%)
1970:Q1-1970:Q4	0.33	-1.47
	(-0.10, 0.80)	(-2.39, -0.47)
1973:Q4-1975:Q1	3.25	-8.96
	(1.76,4.74)	(-11.25, -6.33)
1980:Q1-1980:Q2	0.45	-1.35
	(0.13, 0.96)	(-2.34, 0.28)
1981:Q3-1982:Q4	-4.11	-1.19
	(-5.87, -0.84)	(-4.25, 1.77)
1990:Q4-1991:Q1	-0.72	-1.02
	(-1.05,-0.11)	(-1.75, -0.49)
2001:Q2-2001:Q4	-1.19	0.05
	(-1.54,-0.47)	(-0.88, 0.46)
2008:Q1-2009:Q2	-3.01	-2.39
	(-4.21,-0.83)	(-4.71, -1.43)

GDP Growth and Inflation 20 Quarter Cumulative Impulse Response Functions to Supply and Demand Shocks

	GDP growth	Inflation
Aggregate supply	1.21***	-0.89
	(0.26)	(1.0)
Aggregate demand	-0.05	1.84***
	(0.07)	(0.47)

standard errors in parentheses

Decomposing the Covid Recession

Quarter	GDP Shock (%)	Demand Component (%)	Supply Component (%)
2020:Q1	-6.52	-3.52	-3.00
	(-7.00, -6.08)	(-4.80, -0.96)	(-5.68, -1.80)
2020:Q2	-35.24	-18.28	-16.96
	(-37.04, -34.28)	(-24.60, -4.68)	(-30.60, -10.80)
2020:Q3	19.80	24.88	-5.08
	(-3.32, 36.36)	(8.88, 30.92)	(-25.92, 24.44)
2020:Q4	-4.68	-3.08	-1.60
	(-8.72, -2.20)	(-5.36, -0.04)	(-7.60, 4.96)

Conclusions

- Novel econometric approach to decompose business cycles into aggregate demand and aggregate supply components based on Non-Gaussian features of macroeconomic data
- Minimal theoretical assumptions, data needs, and computational requirements