Aggregate Demand and Aggregate Supply Effects of CoViD-19: A Real-time Analysis

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The expressed views do not necessarily reflect those of the Board of Governors of the Federal Reserve System, or its staff.

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Definitior	าร		

- Following Keynesian tradition (e.g., Blanchard, 1989):
 - Aggregate demand (AD) shocks: move inflation and real activity in the same direction
 - Aggregate supply (AS) shocks: move inflation and real activity in the opposite direction

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Motivatio	n		

- Distinguishing AD from AS shocks is a long-standing goal of macroeconomics (earlier studies include, e.g., Burns and Mitchell, 1946):
 - Fiscal and monetary policy responses usually very different
 - Affect performance of various asset classes differently (Bekaert, Engstrom, Ermolov, 2021)

Modeling Demand and Supply Shocks

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AD/AS Shocks during CoViD-19

- For many recessions the dominant force is immediately clear:
 - Oil crises in the 1970s \Rightarrow supply shocks
 - $\bullet \ \ \text{Volcker experiment} \Rightarrow \text{demand shock}$
- AD-AS decomposition is particularly interesting during CoViD-19: massive lockdowns are large negative demand shocks, but also many supply shocks at the same time...

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Supply Shocks during CoViD-19: Labor force



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ECONOMY | U.S. ECONOMY

Coronavirus Relief Often Pays Workers More Than Work

When combined with state benefits, weekly government payouts create incentives that employers say complicate efforts to reopen businesses



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Supply Shocks during CoViD-19: Domestic production



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Grocers Hunt for Meat as Coronavirus Hobbles Beef and Pork Plants

Surging consumer demand also tightens supplies; supermarkets brace for shortages



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Supply Shocks during CoViD-19: International Supply Chains



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ECONOMY | THE OUTLOOK

Firms Want to Adjust Supply Chains Post-Pandemic, but Changes Take Time

Covid-19 has exposed the risk of farflung production; alternatives like making things at home could raise costs



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1. Trump Hints at Comeback as His Presidency Ends



- 2. iPhone 12 Mini: The Mini Review
- Fauci Says the U.S. Will Remain in the WHO





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Contribut	ion		

- Novel, easily implementable approach to identify demand and supply shocks
- Identification through non-Gaussian features of the data:
 - minimal theoretical assumptions
 - strongly supported by data (e.g., Evans and Wachtel, 1993, for inflation, and Hamilton, 1989, for GDP growth)
- Relies on survey forecast revisions:
 - aggregate measure available in real time
 - no need to model conditional mean
 - good empirical fit (e.g., Ang, Bekaert, and Wei, 2007)

Modeling Demand and Supply Shocks

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Demand and Supply Shocks

• Consider GDP growth and inflation shocks:

•
$$g_{t+1} = E_t[g_{t+1}] + \epsilon_{t+1}^g$$

- $\pi_{t+1} = E_t[\pi_{t+1}] + \epsilon_{t+1}^{\pi}$
- Model them as functions of AD (u^d_t) and AS (u^s_t) shocks:

$$\epsilon_{t+1}^{g} = \underbrace{\sigma_{g}^{d}}_{>0} u_{t+1}^{d} + \underbrace{\sigma_{g}^{s}}_{>0} u_{t+1}^{s},$$

$$\epsilon_{t+1}^{\pi} = \underbrace{\sigma_{\pi}^{d}}_{>0} u_{t+1}^{d} - \underbrace{\sigma_{\pi}^{s}}_{>0} u_{t+1}^{s},$$

$$Cov(u_{t+1}^{d}, u_{t+1}^{s}) = 0, Var(u_{t+1}^{d}) = Var(\underbrace{u_{t+1}^{s}}_{< \Box > < C}) = 1.$$

$$\underbrace{v = Var(u_{t+1}^{s}, u_{t+1}^{s}) = 1}_{0, \forall ar(u_{t+1}^{d}) = \sqrt{2}} \underbrace{v = Var(u_{t+1}^{s})}_{< \Box > < C} \underbrace{v = Var(u_{t+1}^{s})}_{0, \forall ar(u_{t+1}^{s}) = \sqrt{2}} \underbrace{v = Var(u_{t+1}^{s})}_{0, \forall ar(u_{t+1}^{s}) = \sqrt{2} \underbrace{v = Var(u_{t+1}^{s})}_{0, \forall ar(u_{t+1}^{s})}_{0, \forall ar(u_{t+1}^{s}) = \sqrt$$

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Identification 1/3

• Sample covariance matrix:

$$Cov(\epsilon_t^g, \epsilon_t^\pi) = \begin{bmatrix} (\sigma_g^s)^2 + (\sigma_g^d)^2 & -\sigma_\pi^s \sigma_g^s + \sigma_\pi^d \sigma_g^d \\ -\sigma_\pi^s \sigma_g^s + \sigma_\pi^d \sigma_g^d & (\sigma_\pi^s)^2 + (\sigma_\pi^d)^2 \end{bmatrix}$$

- 3 unique moments, but need 4 coefficients to extract AD and AS shocks
- "Demand" and "supply" shocks are not identified in Gaussian framework ⇒ use unconditional higher order moments (in spirit of Lanne, Meitz, and Saikkonen, 2017)

Modeling Demand and Supply Shocks

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Identification 2/3

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

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

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

• Imagine $E[(u_t^s)^3] \approx 0$ and $E[(u_t^d)^3] < 0$:

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

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

• If in data $E[u_t^g(u_t^\pi)^2] < E[(u_t^g)^2 u_t^\pi] \Rightarrow \sigma_\pi^d > \sigma_g^d$

• Co-skewness moments admit identification of σ_{π}^{d} and σ_{g}^{d}

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Identification 3/3

- 12 unconditional moments to match:
 - 3 second order moments: $Std(u_t^g)$, $Std(u_t^{\pi})$, $Corr(u_t^g, u_t^{\pi})$
 - 4 third order moments: $Skw(u_t^g)$, $Skw(u_t^\pi)$, $E[(u_t^\pi)^2 u_t^g]$, $E[u_t^\pi (u_t^g)^2]$
 - **5** fourth order moments: $Kurt(u_t^g)$, $Kurt(u_t^\pi)$, $E[(u_t^\pi)^2(u_t^g)^2]$, $E[(u_t^\pi)^3 u_t^g]$, $E[u_t^\pi(u_t^g)^3]$
- 9 parameters to estimate:
 - 4 AD/AS loadings: σ_g^d , σ_g^s , σ_π^d , σ_π^s
 - 2 unconditional skewnesses: $E[(u_t^d)^3]$, $E[(u_t^s)^3]$
 - 3 unconditional excess (co-)kurtoses: $E[(u_t^d)^4] 3$, $E[(u_t^s)^4] 3$, $E[(u_t^s)^2] 1$

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Extracting	Demand	and	Supply	Shock	S

• Given AD/AS loadings can invert AD/AS shocks from GDP growth and inflation shocks:

$$u_t^d = \frac{\sigma_\pi^s \epsilon_t^g + \sigma_g^s \epsilon_t^\pi}{\sigma_\pi^d \sigma_g^s + \sigma_\pi^s \sigma_g^d}$$

$$u_t^s = \frac{\sigma_\pi^d \epsilon_t^g - \sigma_g^d \epsilon_t^\pi}{\sigma_\pi^d \sigma_g^s + \sigma_\pi^s \sigma_g^d}$$

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GDP Growth and Inflation Shocks

 Extracting US real-time GDP growth and inflation shocks from quarterly mean Survey of Professional Forecasters revisions:

$$u_t^g = E_t[g_t] - E_{t-1}[g_t],$$

$$u_t^{\pi} = E_t[\pi_t] - E_{t-1}[\pi_t]$$



AD/AS Inversion: Matching Moments

	Volatility		Correlation		
	u_t^{π}	u_t^g	$u_t^{\pi} u_t^g$		
Data	0.6361	1.1885	-0.1344		
Standard error	(0.0913)	(0.1448)	(0.1555)		
Fitted value	[0.7083]	[1.3295]	[-0.2776]		
	Skev	vness	Coskev	vness	
	u_t^{π}	u_t^g	$(u_t^{\pi})^2 u_t^g$	$u_t^{\pi}(u_t^g)^2$	
Data	0.2005	-1.2343	-0.7873	0.4309	
Standard error	(0.3712)	(0.3890)	(0.2674)	(0.4884)	
Fitted value	[0.3663]	[-1.4465]	[-0.9808]	[0.4874]	
	Excess	kurtosis	Excess cokurtosis		
	u_t^{π}	u ^g	$(u_t^{\pi})^2 (u_t^{g})^2$	$(u_t^{\pi})^3 u_t^{g}$	$u_t^{\pi}(u_t^g)^3$
Data	1.7280	4.7138	1.9239	-0.5464	-1.6186
Standard error	(0.9813)	(1.3877)	(0.8979)	(1.1467)	(1.5647)
Fitted value	[1.7502]	[4.3216]	[2.6462]	[-1.7761]	[-3.2401]
Test	for joint sigi	nificance of 3	3 rd and 4 th ord	ler moments	
J-stat	25.3618				
<i>p</i> -value	0.26%				
		Overidentific	ation test		
J-stat	2.9781				
<i>p</i> -value	38.74%				

Modeling Demand and Supply Shocks $_{\rm OOOOO}$

Estimation

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AD/AS Inversion: Parameter Estimates

Panel A: Inflation/GDP Growth Shocks Loadings					
	u_t^{π}	u_t^g			
u ^s	-0.4829	1.1802			
	(0.0566)	(0.1129)			
ut ^d	0.5141	0.6035			
	(0.0685)	(0.1064)			
Panel B: Higher-ord	ler Moments	of Supply and Demand Shocks			
	Skewness	Excess kurtosis			
u ^s	-1.9563	6.8535			
	(0.3873)	(1.5692)			
u ^d	-0.6896	1.0062			
-	(0.5413)	(1.6825)			
Co-excess kurtosis	-0.0095				
	(0.2843)				







Estimation

Check 1: Impulse Responses

- Identification relies only on sign restriction and unconditional higher order moments
- Literature mostly uses additional economic restrictions: e.g., demand shocks should not have long-run GDP effects (Blanchard and Quah, 1989)
- Is our identification consistent with such restrictions?

• VAR model is:
$$Y_t = A_0 + A_1 Y_{t-1} + S \begin{bmatrix} u_t^s \\ u_t^d \end{bmatrix} + \epsilon_t$$
, where:

- Y_t vector of revised real GDP growth and inflation
- $[u_t^s, u_t^d]'$ pre-estimated demand and supply shocks

Modeling Demand and Supply Shocks

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Check 1: Impulse Responses

	Contemporaneous (quarter 0) responses					
Shock	Real GDP level	Price level				
Demand	0.19%***	0.33%***				
	(0.22%)	(0.00%)				
Supply	0.32%***	-0.18%***				
	(0.00%)	(99.98%)				
	Cumulative (2	0 quarters) responses				
Shock	Real GDP level	Price level				
Demand	0.00%	1.17%***				
	(52.25%)	(0.00%)				
Supply	0.66%***	-0.45%				
	(0.00%)	(93.95%)				

block-bootstrapped probabilities that impulse response < 0 in parentheses

Check 2: Recession Classifications

- AD component: sum of demand shocks during recession $\times \sigma_g^d$
- AS component: sum of supply shocks during recession $\times \sigma_g^s$

NBER Recession	GDP shock: demand component	GDP shock: supply component
1969Q4-1970Q4	-0.34%	-2.11%
1973Q4-1975Q1	-0.08%	-2.33%
1980Q1-1980Q2	0.72%	-0.51%
1981Q3-1982Q4	-3.63%	0.12%
1990Q4-1991Q1	-0.20%	-0.32%
2001Q1-2001Q4	-1.55%	-0.37%
2008Q1-2009Q2	-1.92%	-0.18%

- First 5 recessions consistent with Gali (1992)
- Great Recession debatable: demand (e.g., Mian and Sufi, 2014) vs supply (e.g., Ireland, 2011, or Mulligan, 2012)

Modeling Demand and Supply Shocks

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Real Time GDP Growth and Inflation Shocks

	Real GDP growth shock	Inflation shock
2020: Q1	-6.6%	-2.7%
2020: Q2	-34.3%	-4.6%
Max(1968Q4-2019Q2)	3.6%	2.7%
Min(1968Q4-2019Q2)	-6.6%	-2.1%
2008Q4	-3.5%	-1.4%

Modeling Demand and Supply Shocks

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Real Time Demand and Supply Shocks

	Demand shock	Supply shock
2020: Q1	-7.1	-1.9
2020: Q2	-24.5	-16.5
Max(1968Q4-2019Q2)	3.0	2.9
Min(1968Q4-2019Q2)	-3.8	-5.6
2008Q4	-3.7	-1.1

Modeling Demand and Supply Shocks

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Real Time GDP Growth Demand and Supply Components

	Real GDP growth	Real GDP growth
	demand component	supply component
2020: Q1	-4.3%	-2.3%
	(0.8%)	(0.2%)
2020: Q2	-14.8%	-19.5%
	(2.6%)	(1.9%)
Max(1968Q4-2019Q2)	1.8%	3.5%
Min(1968Q4-2019Q2)	-2.3%	-6.6%
2008Q4	-2.2%	-1.3%
	(0.4%)	(0.1%)

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Real GDP Growth



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Real GDP Growth Shock



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VAR Impulse Response to 2020:Q2 Demand and Supply Shocks

- Survey forecasts reflect real time expectations of market participants
- What would be impulse response to shock of such composition based on historical data?

• VAR model
$$Y_t = A_0 + A_1 Y_{t-1} + S \begin{bmatrix} u_t^s \\ u_t^d \end{bmatrix} + \epsilon_t$$
, where:

- Y_t vector of final revised real GDP growth and inflation
- $[u_t^s, u_t^d]'$ pre-estimated demand and supply shocks
- ϵ_t residual noise vector

Modeling Demand and Supply Shocks

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VAR Cumulative Real GDP Growth Response to 2020:Q2 Demand and Supply Shocks



Modeling Demand and Supply Shocks

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Cumulative Real GDP Growth: Individual Forecasts - 2020:Q2



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Inflation			
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2020Q2 Forecast Revisions Implied Inflation Shock



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Conclus	ions		

- Novel way to identify AD/AS shocks:
 - Minimal theoretical restrictions (just a sign restriction)
 - Utilizing survey forecast revisions
 - Identification through non-Gaussian features
- CoViD-19 dynamics:
 - 2020Q1 GDP growth shock very large by historical standards: mostly demand-driven
 - 2020Q2 shock extraordinary by historical standards: $\frac{2}{2}$ supply- and $\frac{1}{3}$ demand-driven
- Many applications: contact us with any questions during ◆□ > ◆□ > ◆三 > ◆三 > ○ ○ ○ ○ ○ implementation!

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