Inflation Dynamics During the COVID Era: A High-frequency Approach

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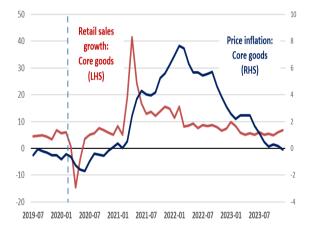
NBER Summer Institute

July 9 2024

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Pandemic led to rapidly evolving economy

Price inflation and retail sales growth of core goods (12-month percent changes)



- Pandemic unleashed an unforeseen shock that led to rapidly evolving economy
- Traditional monthly or quarterly data were not timely enough for real-time decision-making.
- Policymakers turned increasingly to HFIs to assess state of the economy.

High-frequency data: Uncover nonlinearities in COVID inflation dynamics

- We exploit a novel high-frequency panel data set of U.S. retail sales and prices during the COVID era to detect nonlinearities in inflation dynamics in real time.
- First, establish the usefulness of the dataset for inference of aggregate dynamics by examining the correlation with official measures of inflation and retail sales data.
- Second, detect breaks in the PC in real time, using these break dates to explore:
 - 1 Implications for underlying inflation
 - 2 Time-variation in the passthrough of MP to prices and real sales during the pandemic

Main findings

- Identify two breaks in reduced-form PC:
 - Second regime (lockdown, March 2020 July 2021): Steepening
 - Third regime (reopening, July 2021 -): Flattening
- Breaks detected with little delay in real time (6 weeks)
 - ▶ ... and ULI increased: \rightarrow useful for policy makers
- During the lockdown regime, MP had significant effects
 - Large expansionary monetary policy shock traveled fast and was highly effective in preventing deflationary spiral
 - Outside the lockdown regime, the effectiveness of MP is muted.
 - Implies a steepening of structural PC during the lockdown regime.

Data

Weekly data of retail sales and prices of 14 sectors (2020-2023)

- Circana collects some retailers' responses to the Census Bureau's retail trade survey.
 - ▶ cover U.S. retail spending for 150 retailers across all non-grocery store retailers
 - derived from point-of-sale systems at brick and mortar and e-commerce retailers
 - Store types: Total and brick-and-mortar stores
 - Sectors include apparel, footwear, office supplies, tech products, and small appliances
- Informative for retail goods spending (27% of PCE) → highly correlated with official data
 core retail sales (0.9), core goods CPI (0.6)
- > A rich panel dataset of \approx 3,000 observations, a time series of +200 observations
- ▶ Focus on 52-week percent changes to control for seasonal and calendarity effects

Breaks in the Phillips Curve

Applying panel break methods to disaggregate data

- Cross-sectional information can help identify sources of instability in Phillips curves:
 - Sectoral-level data
 - Circumvents the endogeneity problem
- Exploiting cross-sectional information adds power to break tests
 - Time series break tests have weak power
 - Commonality of timing and impact of breaks increases power significantly

Sectoral-level Break Model

As in Smith, Timmermann, and Wright (2023), Phillips curve can shift an unknown number of times (K) at unknown locations τ = (τ₁,...,τ_K)

Breaks assumed to be common, affecting all sectors simultaneously

only identifies breaks to the Phillips curve that are truly common

For sectors i = 1, ..., N and regimes k = 1, ..., K + 1, the breakpoint model is

$$\pi_{it} = \alpha_i + \gamma_t + \rho_k \pi_{it-1} + \lambda_k RS_{it} + \epsilon_{it}, \qquad t = \tau_{k-1} + 1, \dots, \tau_k$$

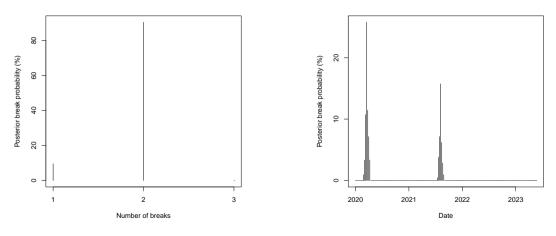
$$\epsilon_{it} \sim N(0, \sigma_{ik}^2)$$

- π_{it} : inflation rate for sector *i* at week *t*
- \triangleright RS_{it}: retail sales for sector *i* at week *t*

Priors and Estimation

- Regime durations have a Poisson prior such that breaks occur, on average, every year
- A Normal-Inverse Gamma prior is specified over the regression coefficients and variances which are relatively uninformative
 - Priors have relatively little influence on posteriors when estimating sectoral Phillips curves with pooled parameters (Jones et al, 2021)
- Each model is estimated using a multi-step reversible jump MCMC algorithm (Smith and Timmermann, 2021)

Breaks in the Phillips curve



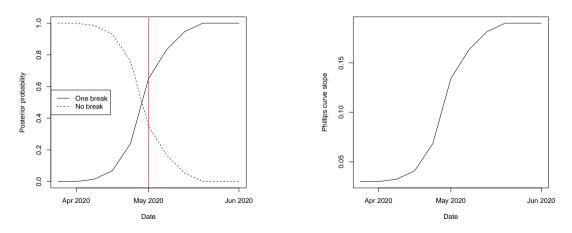
(a) Posterior number of breaks

(b) Posterior timing of breaks

Breaks in the Phillips Curve

	Jan 2020 - Mar 2020	Mar 2020 - Jul 2021	Jul 2021 - Dec 2023	Jan 2020 - Dec 2023
PC	0.03	0.19***	0.01	0.07**
vol.	4.19	8.91	5.54	6.22

Real-time evolution of parameter estimates



(a) Real time evolution of pandemic break probability

(b) Real time evolution of Phillips correlation

Implications for underlying inflation

"Detecting the changing momentum of underlying inflation in real time"

Replacing time FE with (1) LR inflation expectations π^e_{t-1} and (2) a regime-specific constant β_k in PC model:

$$\pi_{it} = \beta_k + \alpha_i + \rho_k \pi_{it-1} + \lambda_k RS_{it} + \gamma_k \pi_{t-1}^e + \epsilon_{it}, \qquad t = \tau_{k-1} + 1, \dots, \tau_k.$$
(1)

ULI π_t^* : Non-transitory persistent component common across π_{it} $(\pi_t^* \approx \pi_{t-1}^*)$

$$\pi_t^* = \beta_k + \rho_k \pi_t^* + \gamma_k \pi_{t-1}^e \quad , \qquad t = \tau_{k-1} + 1, \dots, \tau_k.$$
⁽²⁾

lmpose $\rho_k + \gamma_k = 1$: changes in expectations pass through entirely into actual inflation

► ULI = inflation expectations + regime-specific adjustment factor

$$\pi_t^* = \pi_{t-1}^e + \beta_k / \gamma_k \qquad t = \tau_{k-1} + 1, \dots, \tau_k, \qquad k = 1, \dots, K + 1.$$
(3)

Replacing time FE with (1) LR inflation expectations π^e_{t-1} and (2) a regime-specific constant β_k in PC model:

$$\pi_{it} = \beta_k + \alpha_i + \rho_k \pi_{it-1} + \lambda_k RS_{it} + \gamma_k \pi_{t-1}^e + \epsilon_{it}, \qquad t = \tau_{k-1} + 1, \dots, \tau_k.$$
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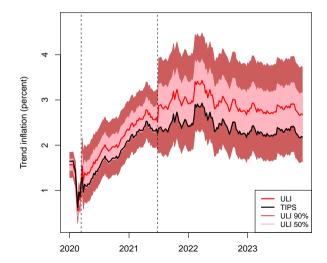
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(2)

• Impose $\rho_k + \gamma_k = 1$: changes in expectations pass through entirely into actual inflation

► ULI = inflation expectations + regime-specific adjustment factor

$$\pi_t^* = \pi_{t-1}^e + \frac{\beta_k}{\gamma_k} \qquad t = \tau_{k-1} + 1, \dots, \tau_k, \qquad k = 1, \dots, K+1.$$
(3)

Underlying inflation



Pass-through of monetary policy shocks

"Was monetary policy effective during the Covid era?"

Time-varying effectiveness of MP during the pandemic

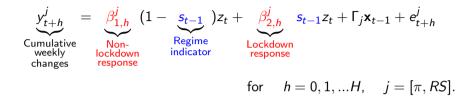
Question and challenge during the fast-evolving pandemic

- Did expansionary MP effectively prevent deflationary spiral?
- Did contractionary MP effectively stabilize inflation?
- Difficult to evaluate policy effectiveness during the fast-evolving COVID era without high-frequency data

Our solution!

- Examine the pass-through of MP to changes in prices and real sales using HFIs
- Condition on regimes identified by the reduced-form PC model
 - ▶ The slope of PC \rightarrow effects of monetary policy (a + demand shock) on P (+) and Q (+).

Local projection with an externally identified shock

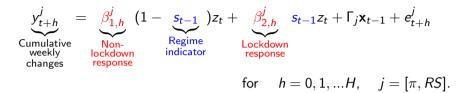


Regime indicator (s_t) : from the reduced-form breakpoint approach

- 1 Lockdown regime ($s_t = 1$) : March 2020 July 2021
- **2** Non-lockdown regime $(s_t = 0)$

Externally identified shock (z_t) : Bu, Rogers, and Wu (2021) Details

Local projection with an externally identified shock



Controls (x_{t-1} , all weekly): 12 lags for macro controls and z_{t-1}

- 1 Weekly changes in prices (π_t) and real sales (RS_t) : 52-week changes divided by 52
 - ▶ Further consider the weekly economic indicator from FRB New York and Dallas for robustness
- 2 Global supply chain pressure index from FRBNY (weekly, interpolated)
- 3 Two-year treasury yield
- 4 Term premium of 10-year zero coupon bond (proxy of excess bond premium)
- 5 Ten-year breakeven inflation rate Data

Time-varying pass-through of monetary policy shocks

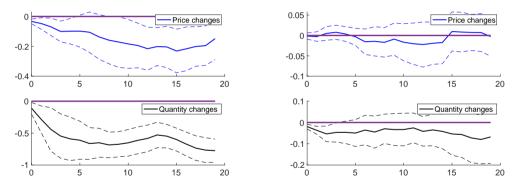
- Lockdown regime : sizable and significant pass-through
- ▶ Non-lockdown regime : weak or insignificant pass-through
- **Brick-and-mortar** stores show faster and larger responses during the lockdown regime.
- ► The results are robust to alternative monetary policy shocks. Jarocinski (Kuttner)

Total: Statistically significant pass-through during the lockdown

Cumulative changes in prices and real sales to a one standard-deviation shock

A: Lockdown regime

B: Non-lockdown regime



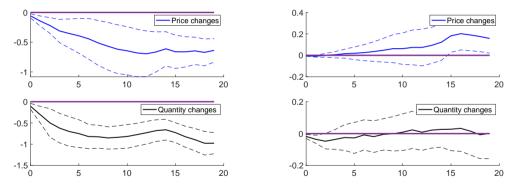
Similar responses of aggregate output and prices to a +25bp monetary policy shock (The data cover 1/5 of real GDP (1/4 of PCE); One standard deviation of BRW shock is 6bp). [-1.5pp: $\uparrow \approx 1\%$ of P (1.2% in Jun.2020 core CPI), $\uparrow \approx 3\%$ of Q (-7.5% in 2020Q2 real GDP)].

Brick and Mortar: Larger effects on harder-hit sectors during lockdown

Cumulative changes in prices and real sales to a one standard-deviation shock

D: Non-lockdown regime

C: Lockdown regime



Covid retail apocalypse: Apparel, footwear, and beauty products show similar patterns (1/3).

Horizon	Average	Lockdown
h=0	0.37**	0.53**
	[0.31,0.43]	[0.52,0.54]
h=4	0.32**	0.50**
	[0.19,0.45]	[0.48,0.49]
h=8	0.30	0.53**
	[0.00,0.61]	[0.42,0.64]
h=16	0.11	0.69**
	[-1.01,0.61]	[0.56,0.83]
h=20	-0.4	0.69**
	[-1.42,0.34]	[0.57,0.80]

Structural Phillips correlation: Brick-and-Mortar Stores

- Structural Phillips curve = AS curve
 - The AS slope is recovered when the AD curve shifts along the AS curve.
- Recover the slope of Phillips curve from the ratio of cumulative responses after MP shocks
 - Barnichon and Mesters (2021); Ahn and Rudd (2024)
- Steepening among brick-and-mortar stores during the lockdown → ↑ Monetary policy effectiveness Total

Policy implications

- During the lockdown, expansionary policy was likely effective in preventing further deceleration in prices and real sales (potentially deflationary spiral).
 - Timely policy likely helped to mitigate credit crunch in sectors hard hit by the Covid-19 shock
 - ▶ Higher attention to economy may have raised MP effectiveness (Ahn and Farmer, 2024).
 - The steepening of structural Phillips curve $\rightarrow \uparrow$ Effects of monetary policy on inflation
- The muted pass-through after the re-opening suggests contractionary monetary policy may not be as effective in stabilizing inflation as in the lockdown regime.
 - Monetary policy alone is unlikely to solve all the inflation problems in the Covid era.
 - \blacktriangleright ULI has increased \rightarrow last mile of disinflation may prove more costly

Conclusions

Conclusions

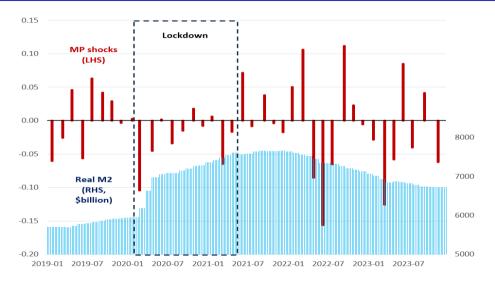
- **1** We exploit a novel high frequency data set of prices and quantities that are highly correlated with official measures of inflation and retail sales
- We document a steepening and subsequent flattening in the reduced (and structural) PC during the pandemic
 - breaks detected with little delay in real time
- **③** Expansionary MP in lockdown regime was highly effective in preventing deflationary spiral
 - muted effectiveness of MP outside this regime
 - ULI has increased

Appendix

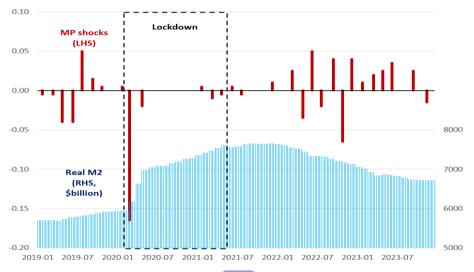
Data Sources: Macro controls

- ▶ NPD data for π_t and RS_t
- The term premium of 10-year zero coupon bond: retrieved from https://fred.stlouisfed.org/series/THREEFYTP10.
- Ten-year breakeven rate, retrieved from https://fred.stlouisfed.org/series/T10YIE.
- Global supply chain pressure index (FRBNY) : Monthly index, interpolated into weekly, retrieved from https://www.newyorkfed.org/research/policy/gscpi#/overview
- Two-year treasury yield, retrieved from https://fred.stlouisfed.org/series/DGS2
- Robustness checks: consider the weekly economic index from FRB of Dallas, retrieved from https://www.dallasfed.org/research/wei

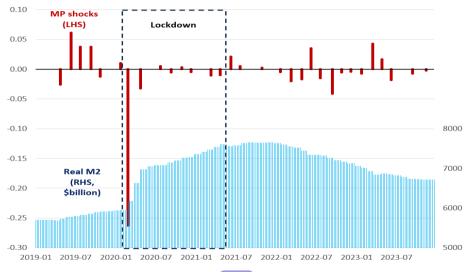
Monetary Policy Shock (BRW) and Real M2 Money Stock



Jarocinski and Karadi (2020)

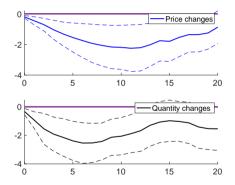


Kuttner (2001)

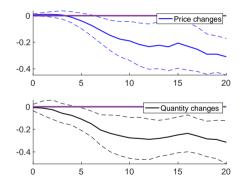


Jarocinski and Karadi (2020): Brick and Mortar

A: Brick and Mortar (lockdown regime)

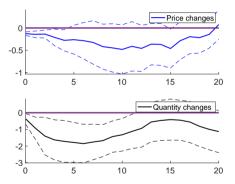


B: Brick and Mortar (non-lockdown)

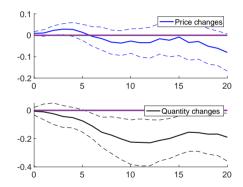


Jarocinski and Karadi (2020): Total

A: Total (lockdown regime)

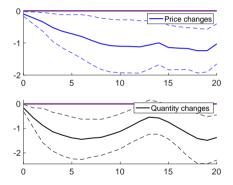


B: Total (non-lockdown)

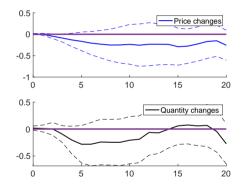


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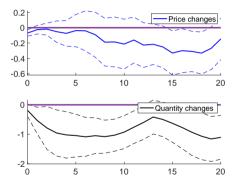


B: Brick and Mortar (non-lockdown)

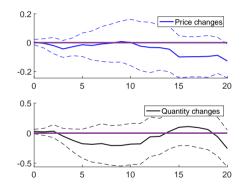


Kuttner (2001): Total

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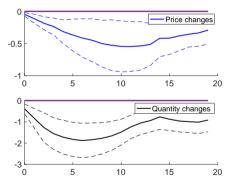


B: Total (non-lockdown)

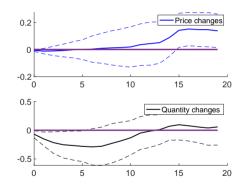


Disaggregate impulse responses: Apparel

A: Lockdown regime



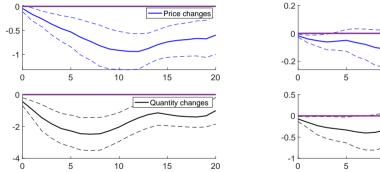
B: Non-lockdown



Disaggregate impulse responses: Footwear

A: Lockdown regime

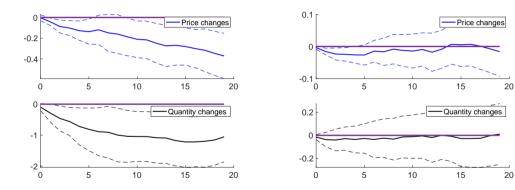
B: Non-lockdown



Disaggregate impulse responses: Beauty product

A: Lockdown regime

B: Non-lockdown



Slope of structural Phillips curve: Total

Horizon Average		Lockdown
h=0	0.17**	0.30**
	[0.06,0.29]	[0.19,0.40]
h=4	0.09	0.19**
	[-0.04,0.23]	[0.19,0.20]
h=8	0.15*	0.19**
	[0.02,0.29]	[0.14,0.25]
h=16	0.22**	0.23**
	[0.06,0.37]	[0.14,0.31]
h=20	0.23**	0.26**
	[0.08,0.39]	[0.17,0.35]

