Demand Composition and the Strength of Recoveries

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Figure: Composition of consumption declines in U.S. recessions from 1960 - 2019 (peak-to-trough) and for the COVID-19 recession (February - May 2020)
Composition of consumption declines in a demand-driven recession determines the strength of the recovery

• Recovery from an ordinary, durables-led recession is stronger than the recovery from an equally deep services-led recession like Covid-19

• Why?
  Basic consumption theory
  + demand-determined output
    • Durable cuts in a recession = depreciated stock of durables in the future
    • After an ordinary durables-led recession, households seek to replenish it
    • This pent-up demand boosts aggregate spending, generating an internal tendency towards recovery that is missing after services-led recessions

• What we do:
  simple model + VAR evidence + quantify $\frac{\partial \text{recovery strength}}{\partial \text{demand composition}}$
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A Simple Model of Pent-Up Demand
Baseline Model

- **Representative household** with preferences over services $s_t$, durables $d_t$ and hours worked $\ell_t$ are represented by the utility function

$$
\mathbb{E}_0 \left[ \sum_{t=0}^{\infty} e^{b^c_t} \left[ e^{b^s_t \phi \rho s_t^{1-\rho}} + e^{b^d_t (1-\phi)^\rho d_t^{1-\rho}} \right]^{\frac{1-\gamma}{1-\rho}} - 1 \right] - \chi \frac{\ell_t^{1+\frac{1}{\phi}}}{1 + \frac{1}{\phi}}
$$

where $b^c_t, b^s_t, b^d_t$ are demand drivers following AR(1) processes

- The **budget constraint** is

$$
p^s_t s_t + p^d_t [d_t - (1-\delta)d_{t-1}] + a_t = w_t \ell_t + e_t + \frac{1 + r^n_t}{1 + \pi_t} a_{t-1} + q_t
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- Model closure: **fully demand-determined output**


  - Market clearing requires $y_t = s_t + e_t$
  - Ensure market clearing through labor rationing (fixed nominal rate & prices)
• **Experiment:** $\rho = \gamma + \text{iid shocks } \{b^c_t, b^d_t, b^s_t\}$. Normalize trough to $-1\%$.

  ○ Look at PDV of output loss as measure of strength of recovery:

  $$y \equiv \sum_{t=0}^{\infty} \beta^t \hat{y}_t$$
Demand Composition and Strength of Recoveries

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1. Pure durables demand shock $b^d_t$: recovery led by pent-up demand

$$\lim_{\beta \to 1} y^d_t = -1 + (1 - \delta) = -\delta$$
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1. Pure service demand shock \( b^s_t \): lost output is never recovered

\[ y^s = -1 \]
Demand Composition and Strength of Recoveries

- **Experiment**: \( \rho = \gamma + \text{iid shocks } \{b^c_t, b^d_t, b^s_t\} \). Normalize trough to -1%.

3. Ordinary recession \( b^c_t \): dominated by pent-up demand effects

\[
\lim_{\beta \to 1} y^c = -1 + \frac{(1 - \phi)}{\phi \delta + (1 - \phi)} (1 - \delta) > -1 + \frac{\bar{e}}{\bar{y}} (1 - \delta)
\]
Demand Composition and Strength of Recoveries

- **Experiment**: $\rho = \gamma + \text{iid shocks } \{b^c_t, b^d_t, b^s_t\}$. Normalize trough to -1%.

4. COVID-19 mix of $b^c_t$ and $b^s_t$: weak pent-up demand
1. **Quadratic adjustment cost (κ) on changes in durables**
   - Delayed adjustment, so depreciation does more of stock adjustment:
     \[-y^d = \sum_{\ell=0}^{\infty} \theta^\ell_d \delta = \frac{1}{1 - \theta_d} \delta\]
     where $\theta_d = \theta_d(\kappa)$ is the persistence of durables holdings
Extensions

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2. **Richer preferences**
   - Continuum of sectors with heterogeneous durability \(\delta_i\): harmonic mean of depreciation rates = overweight durable sectors
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4. **Richer supply side**
   - Partially fixed prices (or wages): V- and Z-shapes similar to baseline
Empirical Evidence
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  - Estimate VAR in output, prices, the ff rate, total consumption and one consumption category at a time (durables, non-durables and services)
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- In paper: other checks (uncertainty, oil, uncond’tl dynamics & spectra)
**Confirm:** Z-cycle for Durables, V-cycle for Services

**Figure:** Quarterly IRFs, with trough response normalized to -1% for all.
Quantification
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2. **Quantitative structural model**
   - **Estimated model,** relaxes fixed prices & fixed shock persistence
Semi-Structural Shift-Share

• Implementation
  ○ **Range**: lower bound is pure services, upper bound is pure durables
  ○ Shares for **avg. recession** and **COVID-19** match historical composition
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Quantitative Model (preliminary!)

- **Framework**: baseline + partially sticky prices + adjustment costs
  - Slope of NKPC follows recent estimates, MP rule is standard
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- Find: service-led recession $\approx 70$ per cent costlier in output PDV
Conclusions & Outlook

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• **Next step**: richer quantitative model, tests in real-time consumption data
Thank you!