Micro to Macro: Applications

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Introduction

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  1. How to estimate aggregate effects of shocks,
  2. How to use knowledge on this to construct counterfactuals
- **Building block:** IRFs of macro variables to shocks, Θ_ℓ.

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- **Building block:** IRFs of macro variables to shocks, Θ_ℓ.
- Why bother with micro evidence? For some questions, aggregate effects are sufficient.
  1. Θ_ℓ is very hard to measure credibly.
     Think about the ideal *macro* experiment for the effects of stimulus checks.
     However, even in an ideal micro set-up, micro evidence only gives *partial* information about Jacobians $\Rightarrow$ need model extrapolation.
  2. Even if we could measure Θ_ℓ, we may be interested in *why* Θ_ℓ is the way it is.
     Besides being interesting by itself, this is potentially important for counterfactuals.
     "Out-of-sample" predictions may depend crucially on micro features, e.g. forward-lookingness in price-setting.

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- **Applications:** answer two question that require micro evidence:

  1. Macro effect of deficit-financed stimulus checks (Angeletos et al., 2023).

  2. Decomposition in direct and indirect effects of monetary policy (Kaplan et al., 2018).

Outline

1. Model Extrapolation: Perpetual-youth OLG + Behavioral Frictions

2. Fiscal Policy: Aggregate effects of Stimulus Checks

3. Monetary Policy: Direct and Indirect effects

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- **TABU/Hybrid-OLG:** tractable alternative to quantitative HANKs.
  If all you care about is matching MPCs, you can do it simpler than HANK. Better for analytical results.
  Different if you care about welfare (Acharya et al., 2023), Dávila-Schaab

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- **Today:** perpetual-youth OLG (Blanchard, 1985; Angeletos et al., 2023)

Example: perpetual-youth OLG from Angeletos et al. (2023)

- **Set-up:** agent i solves

$$\max_{C_{i,t},A_{i,t+1}} \quad \mathbb{E}_t\left[\sum_{k=0}^{\infty}(\beta\omega)^k\left[u\left(C_{i,t+k}\right)-v\left(L_{i,t+k}\right)\right]\right] \tag{1}$$

$$\text{s.t.} \quad A_{i,t+1}=\frac{I_t}{\omega}(A_{i,t}+P_tY_{i,t}-C_{i,t}-T_{i,t}+S_{i,t})), \tag{2}$$

$\omega \leq 1$ is survival probability ($\omega = 1$ is Per. income), $A_{i,t+1}$ nominal assets, $T_{i,t}$ is taxes.

$L_{i,t}$ is chosen by a union so we can ignore it.

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- **Log-linearizing:**

$$c_{i,t} = (1 - \beta\omega) \left(\tilde{a}_{i,t} + \mathbb{E}_t \left[\sum_{k=0}^{\infty} (\beta\omega)^k \left(y_{t+k} - t_{t+k} \right) \right] \right) - \gamma \mathbb{E}_t \left[\sum_{k=0}^{\infty} (\beta\omega)^k r_{t+k} \right]$$

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- **Aggregation.**

$$c_t=(1-\beta\omega)\left[a_t+\mathbb{E}_t\left[\sum_{k=0}^{\infty}(\beta\omega)^k\left(y_{t+k}-t_{t+k}\right)\right]\right]-\gamma\mathbb{E}_t\left[\sum_{k=0}^{\infty}(\beta\omega)^k r_{t+k}\right] \tag{3}$$

Deriving the first column of the Jacobian

- Let $y^d = y_t - t_t$ be disposable income. Want to find $\mathcal{C}_y$ so omit r_{t+1}.
- What is included in the Jacobian, say $\mathcal{C}_y$?

$$\mathcal{C}_y = \begin{pmatrix} \mathcal{C}_{0,0} & \mathcal{C}_{0,1} & \mathcal{C}_{0,2} & \dots \\ \mathcal{C}_{1,0} & \mathcal{C}_{1,1} & \mathcal{C}_{1,2} & \dots \\ \mathcal{C}_{2,0} & \mathcal{C}_{2,1} & \mathcal{C}_{2,2} & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

- Each column is impulse-response to a news shock, "income rises at date s"

Deriving the first column of the Jacobian

- Let $y^d = y_t - t_t$ be disposable income. Want to find $\mathcal{C}_y$ so omit r_{t+1}.
- We can obtain $\mathcal{C}_y$ by solving:

$$c_t + \beta a_{t+1} = a_t + y_t^d$$
$$(1 - \omega(1 - \beta\omega))c_t - \beta\omega c_{t+1} - (1 - \beta\omega)(1 - \omega)a_t = (1 - \beta\omega)(1 - \omega)y_t^d$$

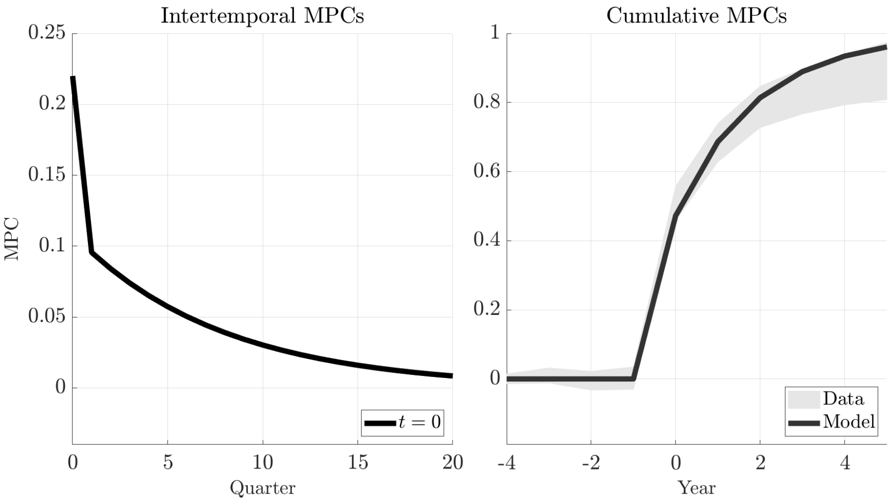
  where the second equation is the Euler Equation version of (3).
- **First column:** $y_0^d = 1$, $y_t^d = 0$ for $t > 0$.
- Can verify that $c_t = (1 - \beta\omega)\omega^t$.
- As argued by Auclert et. al.(2023), this model cannot match iMPCs in the data.
  If we match MPC at 0 $\Rightarrow$ MPC_t decays too fast.
- **Solution:** Add a fraction of "spenders".

Matching the data: Hybrid-OLG

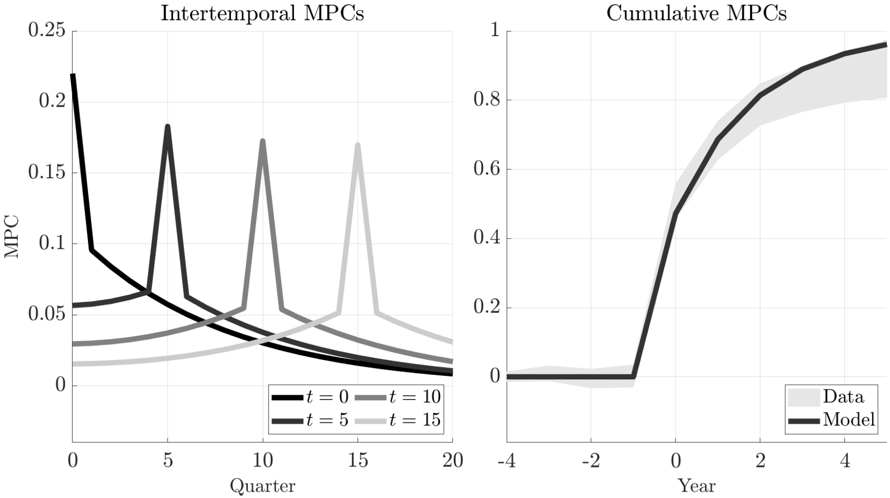
- Fraction μ are spenders, set $c_{i,t} = y^d_{i,t}$.
- Aggregate Jacobian satisfies $\mathcal{C}_y = \mu\mathcal{I} + (1-\mu)\mathcal{C}_y^{OLG}$, $\mathcal{I}$ is the identity matrix.

  Response at 0 is now an ARMA(1,1). AR term comes from OLG, MA term from the spenders.

Matching the data: Hybrid-OLG



Matching the data: Hybrid-OLG - Extrapolation



Changing extrapolation: behavioral frictions

- A natural way of changing extrapolation is adding behavioral frictions.
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- **Recall**: what is included in the Jacobian, say $\mathcal{C}_y$?

$$\mathcal{C}_y = \begin{pmatrix} \mathcal{C}_{0,0} & \mathcal{C}_{0,1} & \mathcal{C}_{0,2} & \cdots \\ \mathcal{C}_{1,0} & \mathcal{C}_{1,1} & \mathcal{C}_{1,2} & \cdots \\ \mathcal{C}_{2,0} & \mathcal{C}_{2,1} & \mathcal{C}_{2,2} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix} \tag{4}$$

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- **How does this generalize?**

Expectation Matrix

- Another way to look at this: how do agents build **expectations** about a date-s shock?
- Define a matrix **E** that, in each column s, has the expectations about a date-s shock.
- How does it look in FIRE and myopic cases?

$$\mathbf{E} = \begin{pmatrix} 1 & 1 & 1 & \dots \\ 1 & 1 & 1 & \dots \\ 1 & 1 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix} \Rightarrow \mathbf{E}^{\text{myopic}} = \begin{pmatrix} 1 & 0 & 0 & \dots \\ 1 & 1 & 0 & \dots \\ 1 & 1 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix} \tag{5}$$

- $E_{t,s} dY_{t,s}$ is the expected value of $dY_{t,s}$ at date t.
- Note: not *all* behavioral frictions can be cast in this form, but some simple and widely used forms can.

General Jacobian Manipulation

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- **Key**: this is a news shock at horizon $\tau - s \Rightarrow$ like column $\tau - s$ of $\mathcal{C}_y$!
- Therefore, column s of $\mathcal{C}_y^{\text{b}}$ are given by:

$$(\mathcal{C}_y^{\text{b}})_{s,t} = \sum_{0}^{\min \tau,s} \underbrace{(E_{\tau,s} - E_{\tau-1,s})}_{\text{expectation revision at } \tau} \times \underbrace{(\mathcal{C}_y)_{\tau-s,s-\tau}}_{\text{effect of shock expected in } \tau - s \text{ periods}} \tag{6}$$

Note: convention is $E_{-1,0} = 0$

Example 1: Sticky Information (Mankiw and Reis, 2002)

- Each date, only a fraction $(1-\theta)$ updates information about news shocks in $t+s$. However, everyone learns the shock at time t.

  Agents know current values of y_t, otherwise could violate constraints (Carroll et al., 2020).

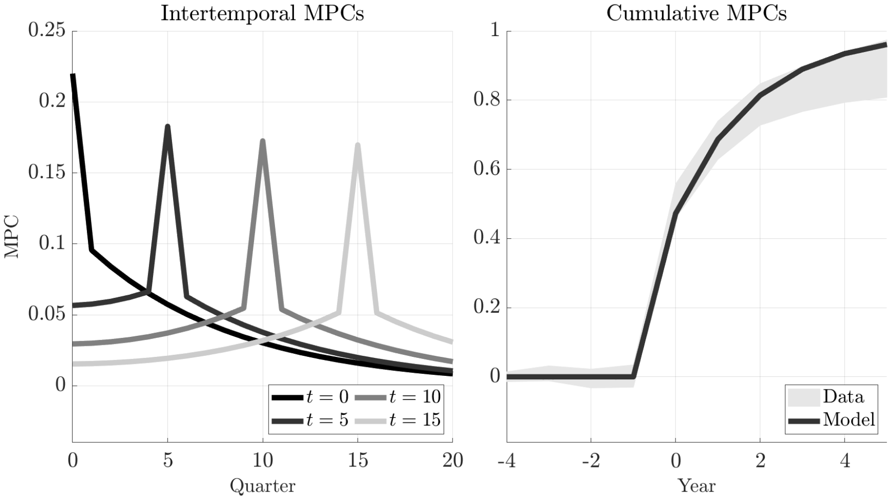
- Expectation matrix is:

$$\mathbf{E} = \begin{pmatrix} 1 & 1-\theta & 1-\theta & \dots \\ 1 & 1 & 1-\theta^2 & \dots \\ 1 & 1 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

- Used in Auclert et al. (2020) to generate "macro humps".

  Sidenote: actually admits recursive representation, faster numerical evaluation.

Compare FI ...


Intertemporal MPCs
MPC
Quarter
0.25
0.2
0.15
0.1
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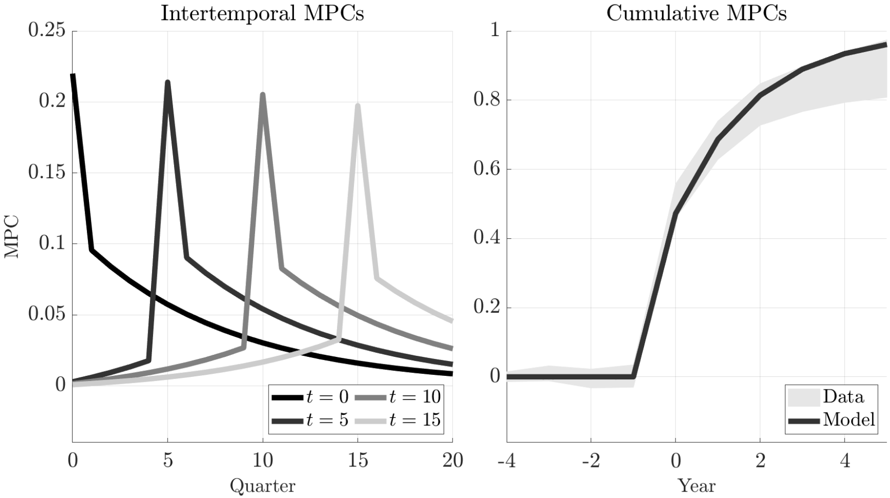
0
0
5
10
15
20
$t = 0$
$t = 10$
$t = 5$
$t = 15$
Cumulative MPCs
Year
1
0.8
0.6
0.4
0.2
0
-4
-2
0
2
4
Data
Model

With Sticky Info: Less Anticipation



Example 2: Cognitive Discouting Gabaix (2020)

- Agents respond to shock h periods in the future as if it was dampened by θ^h
- This is equivalent to assume agents expect shock of size θ^h.
- Expectation matrix is:

$$\mathbf{E} = \begin{pmatrix} 1 & \theta & \theta^2 & \dots \\ 1 & 1 & \theta & \dots \\ 1 & 1 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

- Used in Pfäuti and Seyrich (2023) in the HANK context.

  Sidenote: in GE this kills forward guidance, but unable to generate humps.

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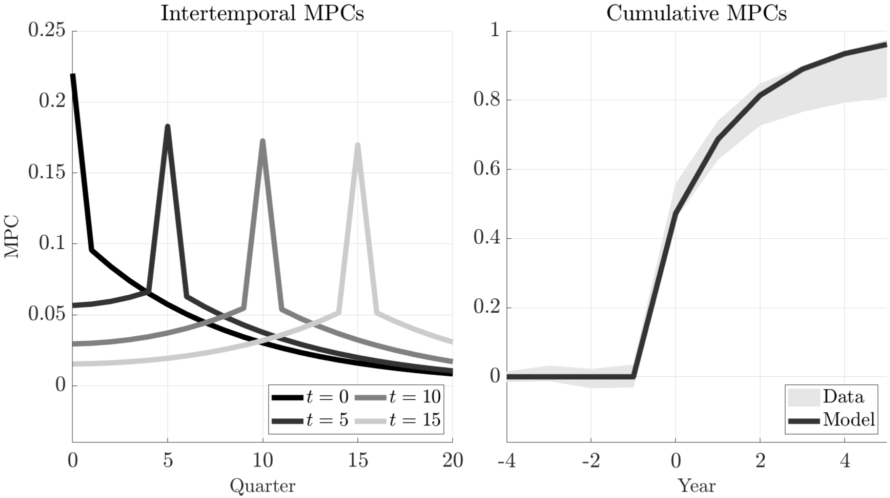

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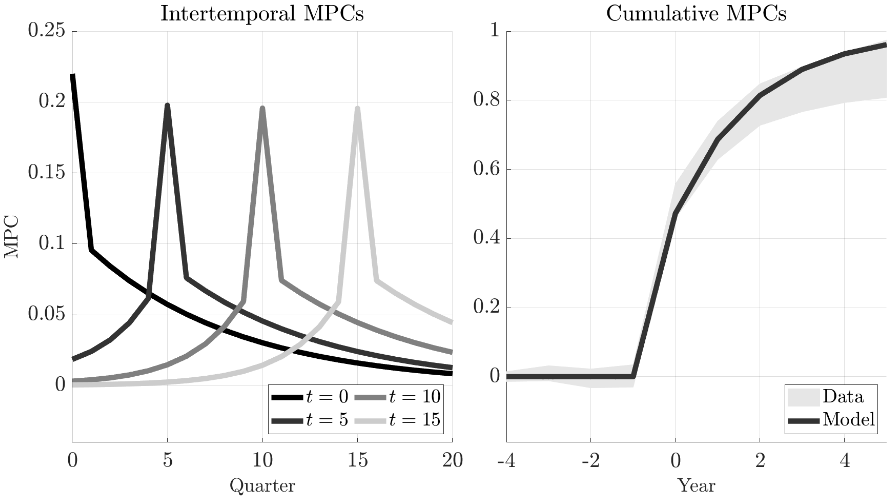
0
-4
-2
0
2
4
Year
Data
Model

With Cognitive Discounting



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"Micro-to-macro" evluation: stimulus checks

- We can use $\mathcal{C}_y$ to obtain the "micro-implied" response to stimulus checks.
- Assume MP keeps real rates constant. Then:

$$
\begin{aligned}
\boldsymbol{C}_y(\hat{\boldsymbol{y}} - \hat{\boldsymbol{\tau}}) &= \hat{\boldsymbol{y}} \\
\hat{\boldsymbol{\tau}} &= \underbrace{\tau_y \hat{\boldsymbol{y}}}_{\text{tax revenue prop. to output}} - \underbrace{\boldsymbol{\varepsilon}}_{\text{stimulus check}}
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Putting both together:

$$\hat{\boldsymbol{y}} = (I - (1 - \tau_y)\boldsymbol{C}_y)^{-1}\boldsymbol{C}_y\boldsymbol{\varepsilon} \tag{7}$$

so again, $\boldsymbol{C}_y$ (plus τ_y) a is sufficient statistic.

If two models agree on $\boldsymbol{C}_y$, then yield identical output response!

Angeletos et al. (2023): self-financing

- Background: self-financing in a “static” Keynesian cross with tax base channel
  - Transfer at $t = 0$, tax (if needed) at $t = 1$, assume static KC at $t = 0$.

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$$y_0 = \frac{\text{mpc}}{1 - \text{mpc}(1 - \tau_y)} \times \text{transfer} \Rightarrow \nu = \frac{\tau_y \text{mpc}}{1 - \text{mpc}(1 - \tau_y)}$$

    where $\nu = \dfrac{\tau_y y_0}{\text{transfer}}$ is self-financed share.
- We see: ν increasing in mpc, with $\nu \to 1$ for mpc $\to 1$

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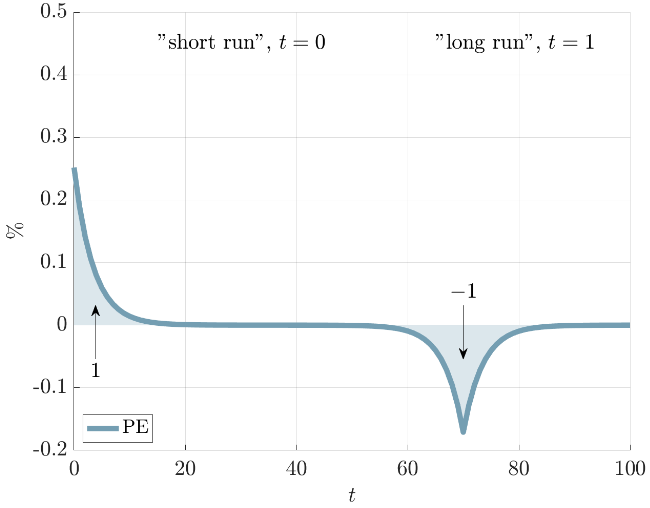
  Assume all debt is repaid with a tax hike at $H >> 0$, and rigid prices.

  PE: Largely discount date-H tax hike + spend date-0 check quickly, so short run PE effect is similar to above with $MPC \to 1$. Then get later demand bust around H.



”short run”, $t = 0$
”long run”, $t = 1$
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
%
1
−1
PE
0
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60
80
100
t

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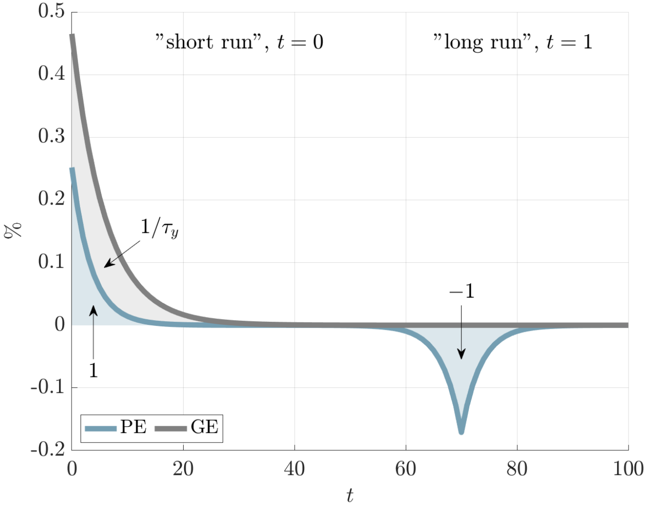
  GE: Spend GE income gains quickly, so multiplier converges to size $1/\tau_y$ quickly—akin to denominator above. Thus debt stabilizes on its own before H, and tax hike is not needed.



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Kaplan et al. (2018): direct and indirect effects

- **Second Application:** With knowledge of $\mathcal{C}_y$, we can also decompose aggregate IRFs into direct and indirect effects.
- Why do we care?
  - If indirect effects are large, mon. pol. relies much more in GE.
    Much more difficult to "fine tune". Opens door for more sources of state-dependence.

Kaplan et al. (2018): direct and indirect effects

- **Second Application:** With knowledge of $\mathcal{C}_y$, we can also decompose aggregate IRFs into direct and indirect effects.
- Why do we care?
  - If indirect effects are large, mon. pol. relies much more in GE.
    Much more difficult to "fine tune". Opens door for more sources of state-dependence.
- From the aggregate consumption function $\mathcal{C}(\boldsymbol{r}, \boldsymbol{y})$, monetary policy shock:

$$\frac{d\hat{\boldsymbol{c}}}{d\varepsilon_0^m} = \underbrace{\boldsymbol{C}_y \frac{d\hat{\boldsymbol{y}}}{d\varepsilon_0^m}}_{\text{indirect effect}} + \underbrace{\boldsymbol{C}_r \frac{d\hat{\boldsymbol{r}}}{d\varepsilon_0^m}}_{\text{direct effect}} \tag{8}$$

- Where $\frac{d\hat{\boldsymbol{c}}}{d\varepsilon_0^m}, \frac{d\hat{\boldsymbol{y}}}{d\varepsilon_0^m}, \frac{d\hat{\boldsymbol{r}}}{d\varepsilon_0^m}$ are IRFs of consumption, output and real rates.
- Thus, knowledge of aggregate IRFs + $\boldsymbol{C}_y$ suffices to compute the decomposition.

Holm et al. (2021) using micro data

- Holm et al. (2021): has access to MP shocks and admin data on households.
- Estimate the decomposition by running:

$$\frac{c_{i,t+h} - c_{i,t-1}}{\bar{c}_{i,t-1}} = \delta_i^h + \beta^h \varepsilon_t^m + \underbrace{\sum_{m=0}^{h} \gamma_m^h \tilde{y}_{i,t+m}^d}_{\text{disposable income}} + \text{controls} \tag{9}$$

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They are careful on what to include in $\tilde{y}_{i,t+m}^d$.

- **Intuition:** by controlling for disposable income, all remaining effect is "direct".

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- When is this valid?

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- When is this valid?
  - Income may be correlated with consumption for other reasons.
    They use lottery prize Fagergeng et al. (2021) IV. Does this solve all problems?

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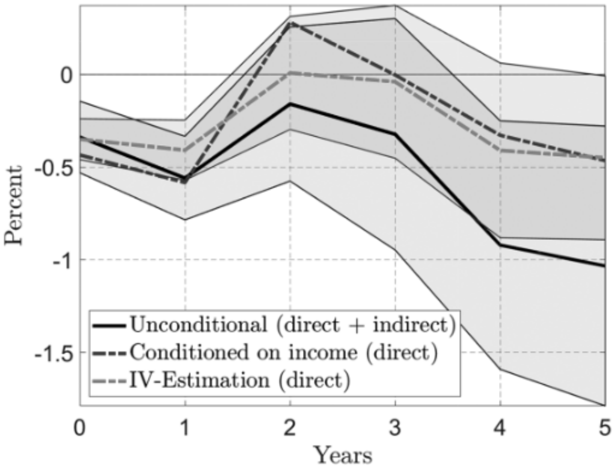
- When is this valid?
  - Income may be correlated with consumption for other reasons.
    They use lottery prize Fagergeng et al. (2021) IV. Does this solve all problems?
  - Only valid if there is no anticipation.
    $\mathcal{C}_y$ would need to be lower-triangular. Otherwise need to control for future income expectations.
    IV based in one-off income gains so does not solve this.

Indirect effect takes time to build up



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Appendix