Lecture 15: Estimating Spillovers

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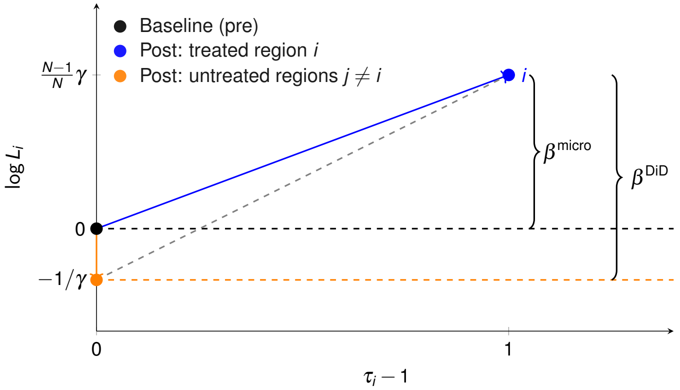
ECON 416-1

Recall from last time

- Three missing intercept problems:
  1. SUTVA-micro violations: Appreciable spillovers on units in control group.
  2. Aggregation: De minimis spillovers in control are economically relevant in aggregate.
  3. SUTVA-macro violations: Treating more units affects aggregate treatment.



Recall from last time

- We discussed three approaches to estimating the "missing intercept" empirically:

1. Sum over all units.
2. Estimate effects across aggregated groups of units.
3. Directly estimate direct effects vs. spillovers.

Directly estimating spillovers: Example from Huber (2018)

TABLE 10—THE DIRECT AND INDIRECT EFFECTS ON FIRM EMPLOYMENT GROWTH

	(1)	(2)
Firm *CB dep*	–0.030	–0.036
	(0.009)	(0.009)
CB dep of other firms in county	–0.166	–0.170
	(0.076)	(0.082)
Observations	48,101	48,101
R^2	0.012	0.017
Firm controls	Yes	Yes
County controls	No	Yes

Notes: This table reports estimates from cross-sectional firm OLS regressions. The outcome is the symmetric growth rate of firm employment from 2008 to 2012. *CB dep* of other firms in county is the average firm Commerzbank dependence of all the other firms in the county. The firm control variables are the same as in Table 4, except there are no county fixed effects. The county controls and the standard error calculations are the same as in Table 8.

- Huber (2018) estimates spillovers using:

  $$Y_{irt} = \beta_1 D_{irt} + \beta_2 D_{(-i)rt} + \varepsilon_{irt},$$

  where

  - D_{irt} is treatment for firm i in region r,
  - $D_{(-i)rt}$ is leave-one-out mean in region.

- Today, we will discuss using this specification to measure spillovers / peer effects.

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Reflection problem: Manski (1993)

- Suppose outcome Y_i is

$$Y_i = \alpha + \eta D_i + \gamma \mathbb{E}[D|X_i] + \beta \mathbb{E}[Y|X_i] + W_i,$$

  where

  - D_i is treatment to unit i,
  - X_i is i's group (e.g., county/region or industry),
  - W_i is an unobserved characteristics, with $\mathbb{E}[W_i|X_i] = \delta X_i$.

- Controlling for own treatment D_i, outcome Y_i may vary with group X_i for three reasons:

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- Controlling for own treatment D_i, outcome Y_i may vary with group X_i for three reasons:
  1. Spillovers through outcomes: i's outcome depends on peers' outcomes: $\beta \mathbb{E}[Y|X_i]$.

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- Controlling for own treatment D_i, outcome Y_i may vary with group X_i for three reasons:

  1. Spillovers through outcomes: i's outcome depends on peers' outcomes: $\beta \mathbb{E}[Y|X_i]$.
  2. Spillovers through treatment: i's outcome depends on peers' treatments: $\gamma \mathbb{E}[D|X_i]$.
  3. Correlated errors: omitted variable varies with group: $W_i = \delta X_i + \varepsilon_i$.

Reflection problem: Manski (1993)

- Outcome:

$$Y_i = \alpha + \eta D_i + \underbrace{\gamma \mathbb{E}[D|X_i]}_{\text{Treatment spillovers}} + \underbrace{\beta \mathbb{E}[Y|X_i]}_{\text{Peer effects}} + \underbrace{W_i}_{\text{Unobs.}}.$$

- What does a regression of Y_i on D_i and $\mathbb{E}[D|X_i]$ yield?

- Taking expectations:

$$\mathbb{E}[Y_i|D_i, X_i] = \alpha + \eta D_i + \gamma \mathbb{E}[D|X_i] + \beta \mathbb{E}[Y|X_i] + \delta X_i.$$

- Right-hand side includes term $\mathbb{E}[Y|X_i]$...

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- Right-hand side includes term $\mathbb{E}[Y|X_i]$...

$$\begin{aligned}\mathbb{E}[Y_i|X_i] &= \alpha + \eta \mathbb{E}[D_i|X_i] + \gamma \mathbb{E}[D|X_i] + \beta \mathbb{E}[Y|X_i] + \delta X_i \\ &= \frac{\alpha}{1-\beta} + \frac{\eta+\gamma}{1-\beta} \mathbb{E}[D_i|X_i] + \frac{\delta}{1-\beta} X_i.\end{aligned}$$

Reflection problem: Manski (1993)

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- Plugging in

$$\mathbb{E}[Y_i|X_i] = \frac{\alpha}{1-\beta} + \frac{\eta+\gamma}{1-\beta}\mathbb{E}[D_i|X_i] + \frac{\delta}{1-\beta}X_i.$$

we find:

$$\mathbb{E}[Y_i|D_i, X_i] = \frac{\alpha}{1-\beta} + \eta D_i + \left(\frac{\eta\beta+\gamma}{1-\beta}\right)\mathbb{E}[D|X_i] + \frac{\delta}{1-\beta}X_i.$$

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- Takeaway:
  - Even if X_i, D_i, and $\mathbb{E}[D|X_i]$ linearly independent, we cannot identify β from γ.
  - What if we included $\mathbb{E}[Y_i|X_i]$ on right-hand side?

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  - Even if X_i, D_i, and $\mathbb{E}[D|X_i]$ linearly independent, we cannot identify β from γ.
  - What if we included $\mathbb{E}[Y_i|X_i]$ on right-hand side?
  - Big problem for literature on peer effects (social norms, peer influence, herd behavior, social interactions, interdependent preferences, ...)

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- Plugging in

$$\mathbb{E}[Y_i|X_i] = \frac{\alpha}{1-\beta} + \frac{\eta+\gamma}{1-\beta}\mathbb{E}[D_i|X_i] + \frac{\delta}{1-\beta}X_i.$$

  we find:

$$\mathbb{E}[Y_i|D_i, X_i] = \frac{\alpha}{1-\beta} + \eta D_i + \left(\frac{\eta\beta+\gamma}{1-\beta}\right)\mathbb{E}[D|X_i] + \frac{\delta}{1-\beta}X_i.$$

- Takeaway:
  - Even if X_i, D_i, and $\mathbb{E}[D|X_i]$ linearly independent, we cannot identify β from γ.
  - What if we included $\mathbb{E}[Y_i|X_i]$ on right-hand side?
  - Big problem for literature on peer effects (social norms, peer influence, herd behavior, social interactions, interdependent preferences, ...)
  - Further problems emerge if X_i, D_i, and $\mathbb{E}[D|X_i]$ are not linearly independent...

Reflection problem: Manski (1993)

$$\mathbb{E}[Y_i|D_i, X_i] = \frac{\alpha}{1-\beta} + \eta D_i + \left(\frac{\eta\beta + \gamma}{1-\beta}\right)\mathbb{E}[D|X_i] + \frac{\delta}{1-\beta}X_i.$$

- What if D_i is linear function of X_i? E.g., $D_i = \phi X_i$.

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- What if D_i is linear function of X_i? E.g., $D_i = \phi X_i$.
  - Then D_i, $\mathbb{E}[D|X_i]$, and X_i are all collinear.
  - Cannot identify direct effects η from spillovers β, γ from correlated unobservables δ.

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- What if $D_i = \phi X_i + \nu_i$?

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- What if $D_i = \phi X_i + \nu_i$?
  - Now we can identify direct effects η...

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$$\mathbb{E}[Y_i|D_i,X_i] = \frac{\alpha}{1-\beta} + \eta D_i + \left(\frac{\eta\beta+\gamma}{1-\beta}\right)\mathbb{E}[D|X_i] + \frac{\delta}{1-\beta}X_i.$$

- What if D_i is linear function of X_i? E.g., $D_i = \phi X_i$.
  - Then D_i, $\mathbb{E}[D|X_i]$, and X_i are all collinear.
  - Cannot identify direct effects η from spillovers β,γ from correlated unobservables δ.
- What if $D_i = \phi X_i + \nu_i$?
  - Now we can identify direct effects η...But still, $\mathbb{E}[D|X_i] = \phi X_i$ is collinear with X_i.

    $$\mathbb{E}[Y_i|D_i,X_i] = \frac{\alpha}{1-\beta} + \eta D_i + \left(\frac{(\eta\beta+\gamma)+\delta/\phi}{1-\beta}\right)\mathbb{E}[D|X_i].$$

  - Cannot identify spillovers β,γ from correlated unobservables δ.
- Latter problem especially relevant to macro. E.g., are correlated firm outcomes due to spillovers or because firms exposed to correlated, unobserved shocks?

Reflection problem: Measurement error

- Let's assume away the problem of correlated unobservables, $\delta = 0$.

$$\mathbb{E}[Y_i|D_i, X_i] = \frac{\alpha}{1-\beta} + \eta D_i + \left(\frac{\eta\beta+\gamma}{1-\beta}\right)\mathbb{E}[D|X_i] + \frac{\delta}{1-\beta}X_i.$$

- Measurement error in treatment variable can bias our estimate of spillovers.

- Some notation:
  - Let $\psi = \alpha/(1-\beta)$ and $\varphi = \frac{\eta\beta+\gamma}{1-\beta}$ be coefficient on $\mathbb{E}[D|X_i]$.
  - Suppose $D_i = \phi X_i + v_i$.
  - Suppose we observe $\tilde{D}_i = D_i + u_i$, where u_i is classical measurement error.

- We want to identify η and φ, but now we observe only $\tilde{D}_i$ and $\mathbb{E}[\tilde{D}|X_i]$.

$$\mathbb{E}[Y_i|D_i, X_i] = \psi + \eta D_i + \varphi\mathbb{E}[D|X_i].$$

Reflection problem: Measurement error

$$\mathbb{E}\left[Y_i|D_i, X_i\right] = \psi + \eta D_i + \varphi \mathbb{E}\left[D|X_i\right].$$

- $\mathbb{E}[\tilde{D}|X_i] = \mathbb{E}[D|X_i] = \phi X_i$, but $\tilde{D}_i \neq D_i$.
- Equivalent to estimating with omitted variable u_i:

$$\mathbb{E}\left[Y_i|D_i, X_i\right] = \frac{\alpha}{1-\beta} + \eta \tilde{D}_i + \varphi\left(\phi X_i\right) - \eta u_i.$$

- How is u_i correlated with variables included in regression?

Reflection problem: Measurement error

$$\mathbb{E}\left[Y_i|D_i,X_i\right]=\psi+\eta D_i+\varphi\mathbb{E}\left[D|X_i\right].$$

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- Equivalent to estimating with omitted variable u_i:

$$\mathbb{E}\left[Y_i|D_i,X_i\right]=\frac{\alpha}{1-\beta}+\eta\tilde{D}_i+\varphi\left(\phi X_i\right)-\eta u_i.$$

- How is u_i correlated with variables included in regression?
  - $Cov\left(\tilde{D}_i,u_i\right)=Cov\left(D_i+u_i,u_i\right)=Var\left(u_i\right)>0.$

Reflection problem: Measurement error

$$\mathbb{E}\left[Y_i|D_i, X_i\right] = \psi + \eta D_i + \varphi \mathbb{E}\left[D|X_i\right].$$

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- How is u_i correlated with variables included in regression?
  - $Cov\left(\tilde{D}_i, u_i\right) = Cov\left(D_i + u_i, u_i\right) = Var\left(u_i\right) > 0.$
  - $Cov\left(\phi X_i - \mathbb{E}\left[\phi X_i|\tilde{D}_i\right], u_i - \mathbb{E}\left[u_i|\tilde{D}_i\right]\right) = -Var\left(u_i\right) < 0.$
  - Estimate of η is going to be biased downward.
  - Estimate of φ is going to be biased upward.

Reflection problem: Measurement error

$$\hat{\eta} = \eta \frac{Var(v_i)}{Var(v_i) + Var(u_i)},$$
$$\hat{\varphi} = \varphi + \eta \frac{Var(u_i)}{Var(v_i) + Var(u_i)}.$$

- Classic attenuation bias in direct effects η.
- Spillovers biased toward direct effect η.
- $\Rightarrow$ measurement errors can lead us to detect spillover effects where they don't exists.
- For intuition, think of case where $Var(u_i)$ is very high.

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Strategic complementarities

- Ball and Romer (1990) show that frictions in nominal price adjustment—e.g., small menu costs—are unable to explain the degree of observed monetary nonneutrality.
- But small nominal frictions $+$ real rigidities can lead to substantial nonneutrality.
- Ball and Romer (1990) consider two specific types of real rigidities.
  - Goods market: Imperfect information with customer markets.
  - Labor market: Firms pay efficiency wages to deter shirking.
- Strategic complementarities in price-setting have become especially popular.
- Large literature trying to measure strength of these strategic complementarities.

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

- Profit function:
$$\pi_i = (p_i - mc_i)\, D_i(\boldsymbol{p}),$$
yields optimal price,
$$\log p_i = \log \mu_i(\boldsymbol{p}) + \log mc_i,$$
where $\log \mu_i(\boldsymbol{p}) = 1/(1 - 1/\sigma_i(\boldsymbol{p}))$.

- Defining
$$\frac{\partial \log \mu_i}{\partial \log p_i} = -\Gamma_i, \qquad \text{and} \qquad \frac{\partial \log \mu_i}{\partial \log p_j} = \Gamma_j \text{ for } j \neq i,$$
we find
$$\begin{aligned} d \log p_i &= -\Gamma_i d \log p_i + \sum_{j \neq i} \Gamma_j d \log p_j + \log mc_i \\ &= \sum_{j \neq i} \frac{\Gamma_j}{1 + \Gamma_i} d \log p_j + \frac{1}{1 + \Gamma_i} \log mc_i. \end{aligned}$$

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

- Defining $\Gamma_{-i} = \sum_{j \neq i} \Gamma_j$, and $d \log p_{-i} = \sum_{j \neq i} (\Gamma_j / \Gamma_{-i}) \, d \log p_j$,

$$\Rightarrow \qquad d \log p_i = \frac{\Gamma_{-i}}{1 + \Gamma_i} d \log p_{-i} + \frac{1}{1 + \Gamma_i} d \log mc_i.$$

- Analogy to reflection problem:
  - Treatment to firm i is change in marginal cost $d \log mc_i$.
  - Peer effects from $d \log p_{-i}$.
- What problems should we anticipate?

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- Analogy to reflection problem:
  - Treatment to firm i is change in marginal cost $d \log mc_i$.
  - Peer effects from $d \log p_{-i}$.
- What problems should we anticipate?
  - Spillovers of outcomes vs. treatments? Not an issue here due to assumptions.
  - $d \log mc_i$ and $\mathbb{E}[d \log p_i]$ collinear (cannot separately identify).
  - Correlated errors: $d \log p_{-i}$ due to unobserved demand shocks also experienced by i.
  - Measurement error: Noise in mc_i will cause us to load on peer effects.

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

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  - $d \log mc_i$ and $\mathbb{E}[d \log p_i]$ collinear (cannot separately identify).
  - Correlated errors: $d \log p_{-i}$ due to unobserved demand shocks also experienced by i.
  - Measurement error: Noise in mc_i will cause us to load on peer effects.
  - Another problem: We also don't know what the weights Γ_j / Γ_{-i} are to construct $d \log p_{-i}$.

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

- Amiti, Itskhoki, and Konings (2019) show that if demand can be written in terms of own price and ideal price index, $D_i(\boldsymbol{p}) = D_i(p_i, P^Y)$, then

$$\Gamma_j / \sum_{k \neq i} \Gamma_k = p_j D_j / \sum_{k \neq i} p_k D_k .$$

$\Rightarrow$ market shares are theoretically correct way to aggregate competitors' prices.

- Moreover, if markup depends only on price relative to index, $\mu_i(p_i/P^Y)$, then $\Gamma_{-i} = \Gamma_i$.

$$d \log p_i = \underbrace{\frac{1}{1+\Gamma_i}}_{\alpha_i} d \log mc_i + \underbrace{\frac{\Gamma_{-i}}{1+\Gamma_i}}_{\gamma_i} d \log p_{-i}. \qquad \Rightarrow \qquad \alpha_i + \gamma_i = 1.$$

- Parameter restriction we can test to see if assumption is reasonable.

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

- What problems should we anticipate?
  1. Spillovers of outcomes vs. treatments? Not an issue here due to assumptions.
  2. $d \log mc_i$ and $\mathbb{E}[d \log p_i]$ collinear.
  3. Correlated errors: $d \log p_{-i}$ due to unobserved demand shocks also experienced by i.
  4. Measurement error: Noise in mc_i will cause us to load on peer effects.
  5. We don't know weights Γ_j / Γ_{-i} to use for $d \log p_{-i}$. Testable restriction $\alpha_i + \gamma_i = 1$.

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

- What problems should we anticipate?
  1. Spillovers of outcomes vs. treatments? Not an issue here due to assumptions.
  2. $d\log mc_i$ and $\mathbb{E}[d\log p_i]$ collinear. $\text{Corr}(d\log mc_i, d\log p_{-i}) = 0.09$.
  3. Correlated errors: $d\log p_{-i}$ due to unobserved demand shocks also experienced by i.
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  4. Measurement error: Noise in mc_i will cause us to load on peer effects.
  5. We don't know weights Γ_j/Γ_{-i} to use for $d\log p_{-i}$. Testable restriction $\alpha_i + \gamma_i = 1$.

- #3–4: Find instruments for $d\log mc_i$ and $d\log p_{-i}$.
  - Instrument for $d\log mc_i$ to address measurement error.
  - Still need instrument for $d\log p_{-i}$ to ensure not capturing correlated demand shocks.

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

- Construct four instruments:
  - Data includes especially granular data on unit values of imported inputs.
  - 1. Foreign-input component of marginal cost (Δmc^*_{it}): expenditure share on imports $\times$ change in import unit values at 8-digit product.
  - 2. For domestic competitors, $\Delta mc^*_{-it} = \sum_{j \neq i} \omega_{jt} \Delta mc^*_{jt}$.
  - 3. For foreign non-Euro competitors, use change in bilateral exchange rates Δe^X_{-it}.
  - 4. For foreign, Euro competitors, use change in export prices to other destinations besides Belgium, Δp^E_{-it}.

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

Table 1: Strategic complementarities: baseline estimates

	OLS		IV		
Dep. var.: Δp_{it}	(1)	(2)	(3)	(4)	(5)
Δmc_{it}	0.348***	0.348***	0.588***	0.650***	0.616***
	(0.040)	(0.041)	(0.094)	(0.112)	(0.103)
Δp_{-it}	0.400***	0.321***	0.549***	0.484***	
	(0.079)	(0.095)	(0.097)	(0.118)	
# obs.	64,823	64,823	64,823	64,823	64,823
Year F.E.	yes	yes	yes	yes	yes
Industry F.E.	no	yes	no	yes	yes
H_0: $\psi + \gamma = 1$	0.747	0.669	1.137	1.133	yes
[p-value]	[0.00]	[0.00]	[0.05]	[0.16]	
Overid J-test χ^2			2.41	0.74	1.44
[p-value]			[0.30]	[0.69]	[0.70]
Weak IV F-test			199.1	154.6	156.3

- Which way do the biases go in OLS? Measurement error? Simultaneity?

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

Table 1b: First-stage regressions

	For column 3		For column 4	
Dep. var.:	Δmc_{it}	Δp_{-it}	Δmc_{it}	Δp_{-it}
Δmc^*_{it}	0.681***	0.167***	0.647***	0.180***
	(0.117)	(0.034)	(0.120)	(0.033)
Δmc^*_{-it}	0.851***	1.355***	0.832***	1.344***
	(0.363)	(0.217)	(0.372)	(0.238)
Δe^X_{-it}	−0.407	0.637***	−0.353	0.695***
	(0.363)	(0.217)	(0.372)	(0.238)
Δp^E_{-it}	0.089	0.481***	0.194	0.438***
	(0.226)	(0.149)	(0.281)	(0.113)
First stage F-test	48.5	79.7	28.9	73.0
[p-value]	[0.00]	[0.00]	[0.00]	[0.00]

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

Table 6: Robustness: alternative measures of competitor prices

	Placebo with random industry assignment		Largest competitor(s)		Placebo with Δmc_{-it}
Dep. var.: Δp_{it}	(1)	(2)	(3)	(4)	(5)
Δmc_{it}	0.949***	0.647***	0.652***	0.628***	0.685***
	(0.101)	(0.139)	(0.114)	(0.100)	(0.155)
Δp_{-it}		0.487***			0.675*
		(0.159)			(0.408)
$S^L_{-it} \cdot \Delta p^L_{-it}$			0.470**	0.394*	
			(0.238)	(0.223)	
$(1 - S^L_{-it}) \cdot \Delta p^{-L}_{-it}$			0.477***	0.639***	
			(0.161)	(0.245)	
$\Delta \tilde{p}_{-it}$	0.036	0.004			
	(0.114)	(0.094)			
Δmc_{-it}					−0.220
					(0.424)
# obs.	64,823	64,823	64,823	64,823	64,780

Notes: All regressions build on the baseline specification in column 4 of Table 1. Columns 1 and 2 add a randomly constructed price index $\Delta\tilde{p}_{-it}$ for fictitious competitors randomly assigned to the industry. Column 3 (4) splits the competitor price index into the price changes for the largest competitor(s) Δp^L_{-it} and the other competitors Δp^{-L}_{-it}, as described in the text and footnote 40. Column 5 includes *domestic* competitor marginal costs Δmc_{-it}.

- $\alpha_i + \gamma_i = 1$ appears satisfied... But can test other aggregations nonparametrically.

Strategic complementarities: Amiti, Itskhoki, and Konings (2019)

- Recall in Atkeson and Burstein (2008) model with Bertrand competition,

$$\sigma_{it} = \rho(1 - S_{it}) + \eta S_{it}.$$

With $\eta = 1$ (Cobb-Douglas across industries), predicts:

$$d\log p_{it} = \left(1 - \frac{\rho - 1}{\rho} S_i\right) d\log mc_{it} + \left(\frac{\rho - 1}{\rho} S_i\right) d\log p_{-it}.$$

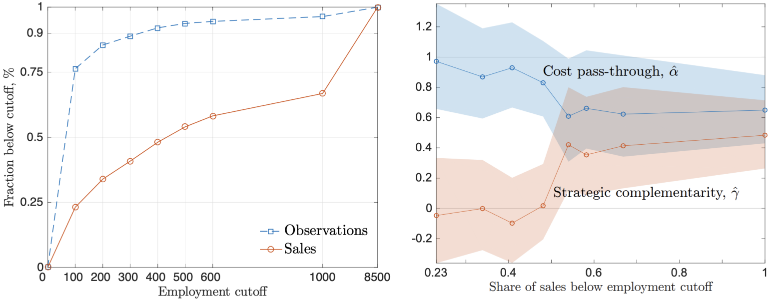

Figure A1: Cost pass-through and strategic complementarity elasticities for different employment-size cutoffs

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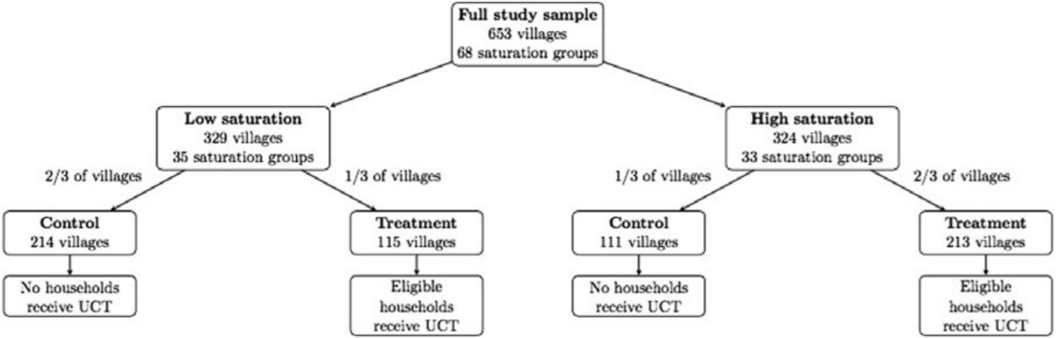
GE spillovers of cash transfers: Egger et al. (2022)

- Egger, Haushofer, Miguel, Niehaus, and Walker (2022) study “cash drop” spillovers.
- GiveDirectly cash transfers of $1000 USD to 10,500 households in 653 villages.



GE spillovers of cash transfers: Egger et al. (2022)

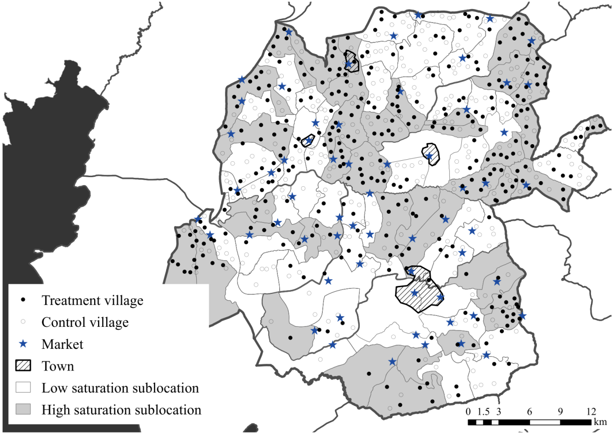


FIGURE A.2.—Study area. *Notes*: This figure plots the approximate location of study villages, sublocation boundaries, and weekly markets in the study area in Siaya County, Kenya. Control villages are denoted by hollow circles, treatment villages are denoted by solid circles, and blue stars indicate the locations of markets. High-saturation sublocations are shaded in gray, while low-saturation sublocations are those in white. Town boundaries are shaded with diagonal lines.

GE spillovers of cash transfers: Egger et al. (2022)

TABLE I

EXPENDITURES, SAVINGS AND INCOME.

	(1)	(2)	(3)	(4)
	Recipient Households		Non-Recipient Households	
	$\mathbb{1}$(Treat Village) Reduced Form	Total Effect IV	Total Effect IV	Control, Low-Saturation Mean (SD)
Panel A: Expenditure				
Household expenditure, annualized	293.59	338.57	334.77	2536.01
	(60.11)	(109.38)	(123.20)	(1933.51)
Non-durable expenditure, annualized	187.65	227.20	317.62	2470.69
	(58.59)	(99.63)	(119.76)	(1877.23)
Food expenditure, annualized	72.04	133.84	133.30	1578.05
	(36.96)	(63.99)	(58.56)	(1072.00)
Temptation goods expenditure, annualized	6.55	5.91	−0.68	37.07
	(5.79)	(8.82)	(6.50)	(123.54)
Durable expenditure, annualized	95.09	109.01	8.44	59.41
	(12.64)	(20.24)	(12.50)	(230.83)
Panel B: Assets				
Assets (non-land, non-house), net borrowing	178.78	183.38	133.06	1131.66
	(24.66)	(44.26)	(78.33)	(1419.70)
Housing value	376.92	477.29	80.65	2032.11
	(26.37)	(38.80)	(215.81)	(5028.27)
Land value	51.28	158.47	544.85	5030.03
	(186.22)	(260.91)	(459.57)	(6604.66)

- "Reduced form" specification and spillover specification for eligible households:

$$y_{ivs} = \alpha_1 \text{Treat}_v + \alpha_2 \text{HighSat}_s + \delta y_{ivs,t=0} + \varepsilon_{ivs},$$

$$y_{ivs} = \alpha + \beta \text{Amt}_v + \sum_{r=2}^{R} \beta_r \text{Amt}_{vr}^{-v} + \delta y_{ivs,t=0} + \varepsilon_{ivs}.$$

- For non-recipient households (eligible hh's in control villages and ineligible hh's):

$$y_{ivs} = \alpha + \sum_{r=2}^{R} \beta_r^1 \text{Amt}_{vr} \left(1 + \beta_r^2 \text{Elig}_{iv}\right) + \delta y_{ivs,t=0} + \gamma \text{Elig}_{iv} + \varepsilon_{ivs}.$$

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Aggregate income vs. aggregate markups

- Markups paid by households increase with their income (elasticity of 2–3%).

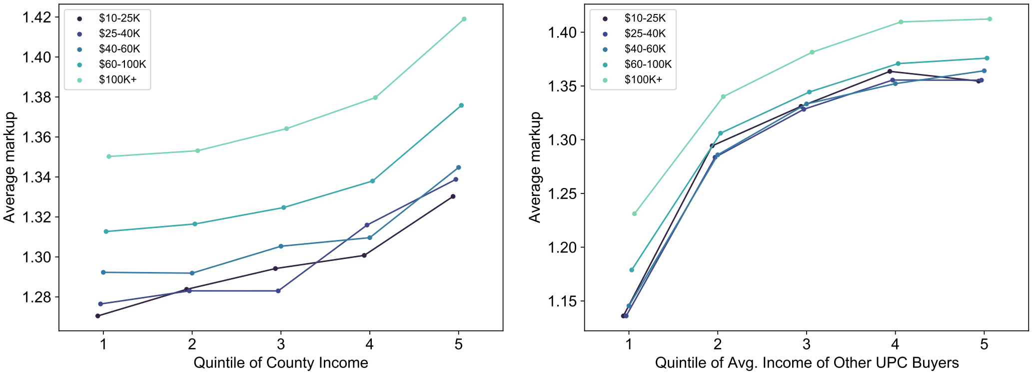
- Does this tell us how markups change in economy when agg. income rises?

- Suppose markups depend on own and agg. income, $\mu_i(z_i, z_{-i})$. Then:

$$\frac{\partial \log \mu^{\text{agg}}}{\partial \log z} \approx \underbrace{\mathbb{E}_c\left[\frac{\partial \log \mu_i}{\partial \log z_i}\right]}_{\substack{\text{“Micro”}\\ \text{elasticity}\\ \text{(2-3\%)}}} + \underbrace{\mathbb{E}_c\left[\frac{\partial \log \mu_i}{\partial \log z_{-i}}\right]}_{\text{Spillovers}}.$$

  - If markups depend on relative income, macro $= 0 <$ micro elasticity.
  - Perfect price discrimination: zero spillovers, macro $=$ micro elasticity.
  - Imperfect price discrimination: positive spillovers, macro $>$ micro elasticity.

Aggregate income vs. aggregate markups



- Descriptive evidence suggests positive spillovers of others’ incomes on prices.
- But... (1) Local costs, (2) income measurement error, (3) correlated hh unobservables.

Identifying spillovers

- Construct retail markups using wholesale cost data from 2006–2012.

- Exploit time series variation in other buyers' incomes (with household & store FEs).

Identifying spillovers

- Construct retail markups using wholesale cost data from 2006–2012.
- Exploit time series variation in other buyers' incomes (with household & store FEs).
- Three designs:

$$\log \text{Markup}_{istk} = \beta_1 \log \text{CBSA Income}_{\text{CBSA}(i,t),t} + \gamma_{i,\text{Income}(i,t)} + \alpha_s + \delta_t + \varepsilon_{istk}.$$

$$\log \text{Markup}_{istk} = \beta_2 \log \text{Income at Retailer Locations}_{\text{Retailer}(s),t} + \gamma_{it} + \alpha_s + \phi_{\text{County}(s),t} + \varepsilon_{istk}.$$

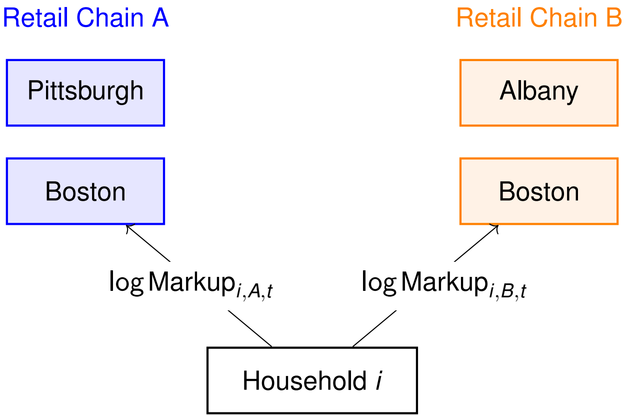
$$\log \text{Markup}_{istk} = \beta_3 \log \text{Income of UPC Buyers}_{\text{UPC}(k),t} + \gamma_{it} + \psi_{st} + \varepsilon_{istk}.$$

for transaction k by household i at store s in year t.

- Controls for unobserved household characteristics (γ_{it}), store-level costs (α_s), time-varying local costs (e.g., $\phi_{\text{County}(s),t}$, ψ_{st}).

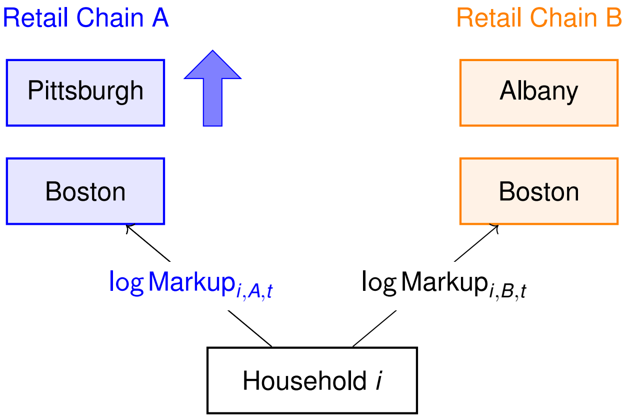
Identifying spillovers: Example

$$\log \text{Markup}_{istk} = \beta_2 \log \text{Income at Retailer Locations}_{\text{Retailer}(s),t} + \gamma_{it} + \alpha_s + \phi_{\text{County}(s),t} + \varepsilon_{istk}.$$



Identifying spillovers: Example

$$\log \text{Markup}_{istk} = \beta_2 \log \text{Income at Retailer Locations}_{\text{Retailer}(s),t} + \gamma_{it} + \alpha_s + \phi_{\text{County}(s),t} + \varepsilon_{istk}.$$



Consistent, positive spillovers across specifications: Macro elasticity 8–15%

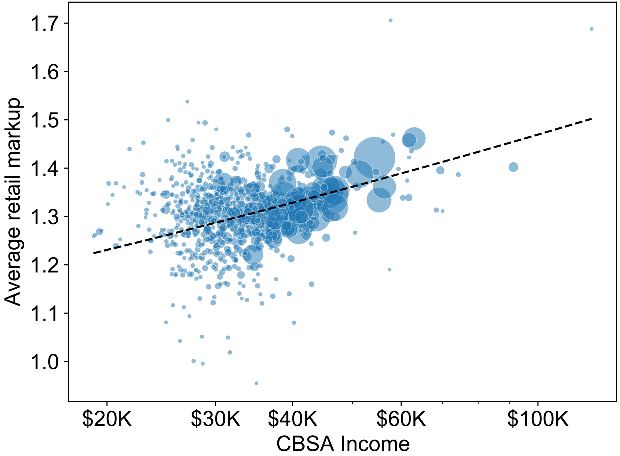
Log Retail Markup	(1)	(2)	(3)
Log Income at Retailer's Locations	0.063**		
	(0.026)		
Log CBSA Income		0.070**	
		(0.012)	
Log Income of Other UPC Buyers			0.142**
			(0.012)
Fixed effects	Household-Year, Store, County-Year	Household-Income, Store, Year	Household-Year, Store-Year
N (millions)	50.9	91.9	97.0
R^2	0.21	0.19	0.21

Regression weighted by sales. SEs two-way clustered by brand & county.

- Macro elasticity $=$ 2–3% (elasticity to own income) $+$ 6–14% (spillovers).

Macro elasticity of 8–15% consistent with markups across CBSAs

Figure: CBSA average retail markup vs. income.



- Elasticity across CBSAs = 11%.
- Rent/wage data suggest bias from local costs is small.
- Trade: Elasticity of markups to income at export destination = 12–24% (e.g., Simonovska 2015).

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Spillovers in a structural model

- In some contexts, we have a structural model of spillovers.

- E.g., we discussed models of input-output networks in which

$$d \log p_i = \sum_j \Psi_{ij} d \log A_j.$$

$$d \log \lambda_i = -\sum_{j=0}^{N} (\theta_j - 1) \lambda_j Cov_{\Omega^{(j)}} (\Psi_{(i)}, d \log p).$$

  Combining yields an expression for $d \log \lambda_i / d \log A_j$ in terms of the input–output structure and elasticities of substitution θ_j.

- Idea: Use exogenous shock to $d \log A$ and input–output matrix to identify θ.

- Then we can use structural model to calculate aggregate counterfactuals.

Spillovers in a structural model: Carvalho et al. (2021)

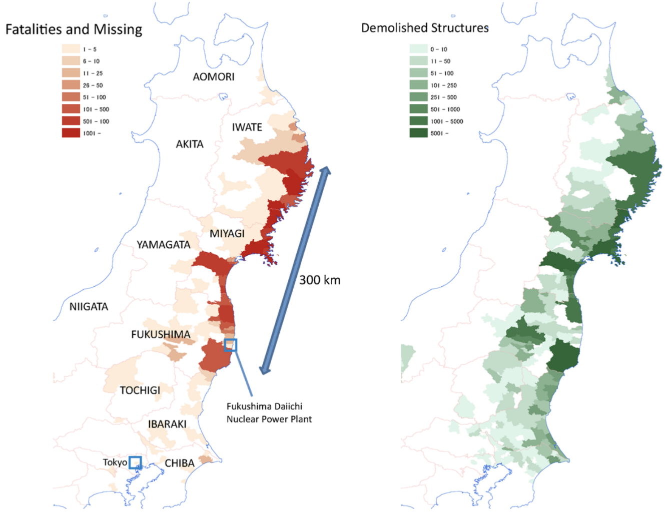


FIGURE I

- Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021) study March 2011 Japan earthquake.
- Detailed data on firm-level supply chain relationships.

Spillovers in a structural model: Carvalho et al. (2021)

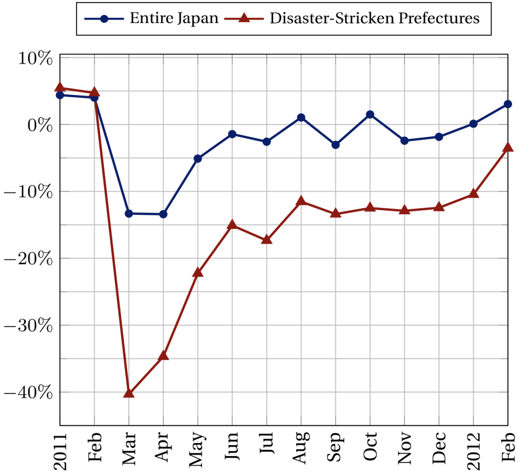
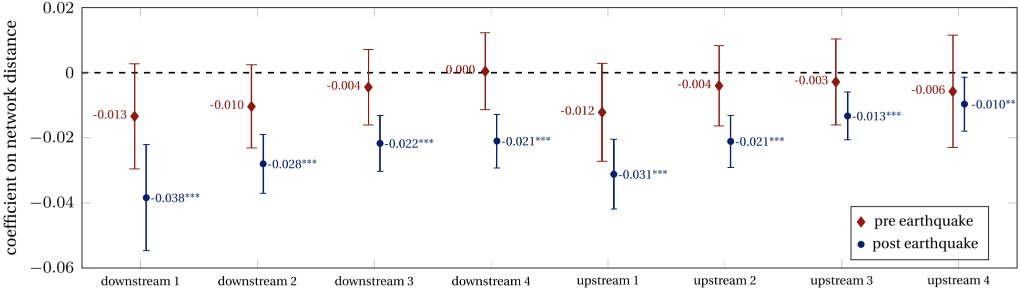


FIGURE II

Growth Rate of Index of Industrial Production

- Real GDP growth rate for four most affected prefectures from 2011–2012 was 2.2pp lower than prior year.
- Four directly affected prefectures account for only 4.6% of output.
- Missing intercept:
  $0.046 \times -2.2\text{pp} = -0.1\text{pp}$.
  In reality, Japan's real GDP growth fell 0.4pp.

Spillovers in a structural model: Carvalho et al. (2021)



- Proof-of-concept: Are firms linked through network more/less affected?

$$\log \text{Sales}_{ipst} = \gamma_i + \gamma_{pst} + \sum_{\tau \neq 2011} \sum_{k} \beta_{k,\tau} \times 1\{i \text{ in group } k\} + \sum_{\tau \neq 2011} \delta_t X_{ips,2010} + \varepsilon_{ipst}.$$

- $\beta_{k,2012} < 0$. Insignificant $\beta_{k,2010}$ (negative suggests faster pre-earthquake growth).

Spillovers in a structural model: Carvalho et al. (2021)

- Suppose A_i shocks to capital stock; elasticity ξ across intermediates and σ across materials vs. value-added:

$$y_i = \left[(1-\omega)\left((A_i K_i)^{\alpha} L_i^{1-\alpha}\right)^{\frac{\sigma-1}{\sigma}} + \omega M_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \qquad M_i = \left[\sum_j \tilde{\omega}_{ij} x_{ij}^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi}{\xi-1}}.$$

- Then:

$$d\log\lambda = (\sigma-1)\Sigma(d\log A) + (\xi-1)\Xi(d\log A),$$

where Σ and Ξ are matrices that capture network exposure. Estimate:

$$\log \text{Sales}_{it} = \gamma_i + \gamma_t + \beta_1\left(\Sigma_i \times d\log A_{2012}\right) + \beta_2\left(\Xi_i \times d\log A_{2012}\right) + \varepsilon_{it},$$

assuming $d\log A_{2012} = -32.5\%$ for firms in disaster areas.

Spillovers in a structural model: Carvalho et al. (2021)

TABLE III

ESTIMATION OF ELASTICITIES OF SUBSTITUTION

		Capital destruction rate		Intermediate input share		Uniform-weighted network
	Baseline	Low	High	Low	High	
	(1)	(2)	(3)	(4)	(5)	(6)
σ	0.595***	0.400***	0.694***	0.556***	0.639***	0.570***
	(0.062)	(0.091)	(0.047)	(0.077)	(0.051)	(0.062)
ξ	1.183***	1.271***	1.138***	1.287***	1.111***	1.155***
	(0.034)	(0.051)	(0.026)	(0.049)	(0.024)	(0.034)

Notes. The table reports estimates for the elasticities of substitution implied by regression specification (7), with robust standard errors reported in parentheses. *, **, and *** denote significance for the null hypothesis of the estimate being equal to 1 at the 10%, 5%, and 1% levels, respectively.

- Substitutability across intermediate inputs: $\xi = 1.2$. Complementarity between materials and value-add: $\sigma = 0.6$.

Spillovers in a structural model: Carvalho et al. (2021)

- Now that we have structural model, we can discipline the missing intercept.
- Recall that

$$\Delta \log Y = \underbrace{\lambda' d\log A}_{0.046\times -2.2\text{pp}\approx -0.1\text{pp}} + \underbrace{\frac{1}{2}(d\log A)'\frac{d\lambda}{d\log A}(d\log A)}_{\text{Network structure}}.$$

- Using network structure, σ, and ξ, $\Delta \log Y \approx -0.47$pp.

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Nontradables vs. tradables

- Idea: Local shock affects local spending on nontradables.
- In aggregate closed economy, everything is nontradable.
- With homotheticity, the proportional response of nontradable spending thus also gives response of tradable spending to aggregate shock.

Nontradables vs. tradables: Chodorow-Reich, Nenov, and Simsek (2021)

- Chodorow-Reich, Nenov & Simsek (2021) study effect of stock wealth on consumption.
- Motivation: Central bankers often argue that stock market fluctuations important because of consumption–wealth effect.
    - *"We care about financial conditions not for themselves, but instead for how they can affect economic activity[...] A rise in equity prices can boost household wealth, which is one factor that underpins consumer spending"* (William Dudley, NY Fed Pres., March 2017).
    - Cieslak and Vissing-Jorgensen (2017) document that $\approx$ 40% of stock market mentions in FOMC minutes take on "driver view"—stock market fluctuations affect economy—with 22% of mentions on consumption-wealth effect.
    - Mentions of stock market in FOMC minutes strongly predictive of future policy (Fed put).
- How large is aggregate effect of stock market fluctuations on consumption?

Nontradables vs. tradables: Chodorow-Reich, Nenov, and Simsek (2021)

- Model: Each area a contains stock-holders (s) and hand-to-mouth h households.

- Cobb-Douglas preferences over nontradables (N) and tradables (T), with prod. tech.:

$$
\begin{aligned}
C_{at}^{i} &= \left(C_{aNt}^{i}\right)^{\eta}\left(C_{aTt}^{i}\right)^{1-\eta}, \\
Y_{at}^{N} &= \left(K_{at}^{N}\right)^{\alpha^{N}}\left(L_{at}^{N}\right)^{1-\alpha^{N}}, \\
Y_{at}^{T} &= \left(K_{at}^{T}\right)^{\alpha^{T}}\left(L_{at}^{T}\right)^{1-\alpha^{T}}, \\
Y_{t}^{T} &= \left(\int_{a}\left(Y_{at}^{T}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}.
\end{aligned}
$$

- Starting at $t=1$, tradables can be produced exclusively with capital at productivity D, so period 0 capital price Q_0 driven by future capital productivity.

Nontradables vs. tradables: Chodorow-Reich, Nenov, and Simsek (2021)

- Stockholders s provide labor inelastically, choose consumption to maximize

$$\sum_{t=0}^{\infty}(1-\rho)^t \log C_{at}^s.$$

- Hand-to-mouth households have elastic labor supply, leading to reduced form

$$d\log w_a = \lambda\left(d\log P_a + \varphi d\log L_a\right).$$

  - λ can reflects wage stickiness.
  - φ reflects effective inverse labor supply elasticities across all households.

- Using $d\log p_a = \eta(1-\alpha^N)d\log w_a$, we have:

$$d\log w_a = \underbrace{\frac{\lambda\varphi}{1-\lambda\eta(1-\alpha^N)}}_{\kappa} d\log L_a.$$

Nontradables vs. tradables: Chodorow-Reich, Nenov, and Simsek (2021)

- In response to shock to D and thus to capital price Q_0 (setting $\varepsilon = 1$):

$$d\log(w_a L_a) = \mathcal{M}(1-\alpha^N)\eta\rho\frac{x_a \Delta Q_0}{W_a L_a}. \qquad \text{(Total payroll)}$$

$$d\log\left(w_a L_a^N\right) = \mathcal{M}(1-\bar{\alpha})\rho\frac{x_a \Delta Q_0}{W_a L_a}. \qquad \text{(Nontradable payroll)}$$

$$d\log(wL) = \mathcal{M}^{\text{agg}}(1-\bar{\alpha})\rho\frac{\Delta Q_0}{WL}. \qquad \text{(Aggregate effect)}$$

where local and aggregate multipliers (in terms of elasticity of local and agg. wage adjustment κ and κ^{agg}) are:

$$\mathcal{M} = \frac{1}{1-(1-\alpha^N)\eta\frac{1+\theta\kappa+\rho(1-\theta)\kappa}{1+\kappa}},$$

$$\mathcal{M}^{\text{agg}} = \frac{1}{1-(1-\bar{\alpha})\frac{1+\theta\kappa^{\text{agg}}+\rho(1-\theta)\kappa^{\text{agg}}}{1+\kappa^{\text{agg}}}-\bar{\alpha}\rho},$$

This is still pretty complicated... but turns out $\mathcal{M}^{\text{agg}} > \mathcal{M}$. Spending on tradables dampens local but not aggregate multiplier.

Nontradables vs. tradables: Chodorow-Reich, Nenov, and Simsek (2021)

- So if preferences homothetic across tradable and nontradable sectors, response of nontradables to local stock market wealth identifies agg. effect up to difference in local vs. aggregate spending multipliers.

Nontradables vs. tradables: Chodorow-Reich, Nenov, and Simsek (2021)

- So if preferences homothetic across tradable and nontradable sectors, response of nontradables to local stock market wealth identifies agg. effect up to difference in local vs. aggregate spending multipliers.

- Evidence of homotheticity across tradable vs. nontradable sectors:

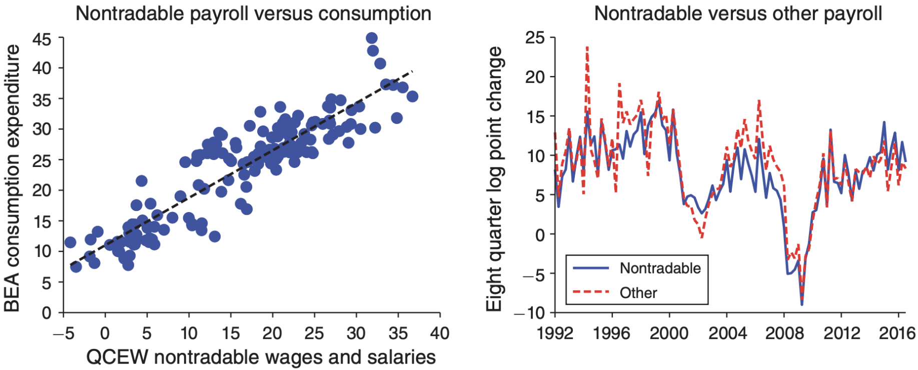

FIGURE 6. NONTRADABLE PAYROLL, CONSUMPTION EXPENDITURE, AND TOTAL PAYROLL

Nontradables vs. tradables: Chodorow-Reich, Nenov, and Simsek (2021)

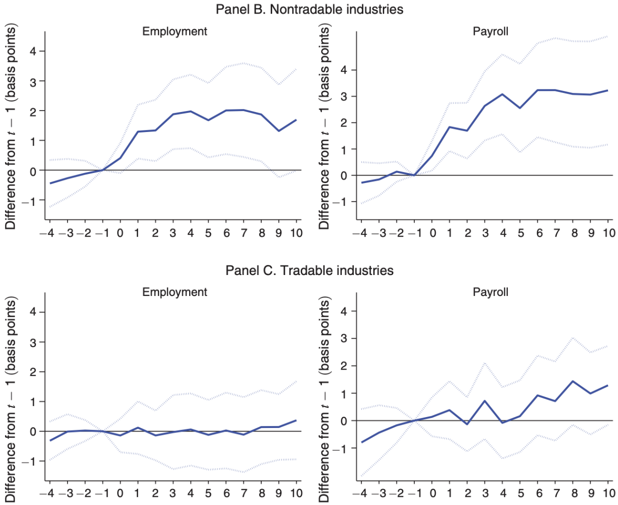

FIGURE 2. BASELINE RESULTS

- Estimate effects on employment/payroll:

$$\Delta Y_{a,t-1,t+h} = \beta_h S_{a,t-1} R_{a,t-1,t} + \gamma_h X_{a,t-1} + \varepsilon_{a,t-1,t+h}.$$

  Identification: stock market returns $R_{a,t-1,t}$ are plausibly exogenous.

- MPC: 3.2 cents of stock wealth.

- Suggests 20% increase in stock valuations increase aggregate payroll by $\geq 1.7\%$.

Summary

- When estimating spillovers directly, need to reckon with reflection problem:
  - Cannot separate spillovers of peers' treatments and peers' outcomes.
  - Correlated unobserved shocks in group.
  - Spurious spillovers due to measurement error in treatment.
- Several examples of how one can overcome this:
  - Instruments, randomization, exploiting additional variation.
- Other approaches: discipline spillovers through structural model.
  - E.g., input–output linkages, nontradables vs. tradables.