Do localised lockdowns generate labour market spillovers?

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Context

- Covid-19 $\rightarrow$ large fall in U.S. employment (15% at peak)
- Lockdowns/business closures as non-pharmaceutical measures
- Federal advisory strategy, implementation left to states/counties
  $\implies$ patchwork of lockdowns

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  $\implies$ **patchwork of lockdowns**

Motivation

- 25% of U.S. workers commute across counties (ACS data)
- 33% of restaurants' visitors comes from a different county (Safegraph, 2019)

- $\implies$ Local measures have spatial effects
  Local + spillovers

- Not taking these into account $\implies$
  1. Biased empirical estimations
  2. Wrong conclusions about optimal lockdowns?
  3. Were fiscal policies ill-targeted?

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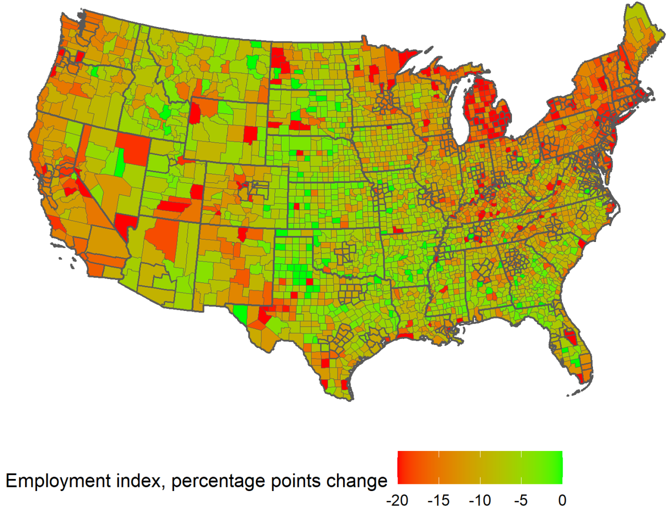
Economic question

How important are lockdown spillovers?

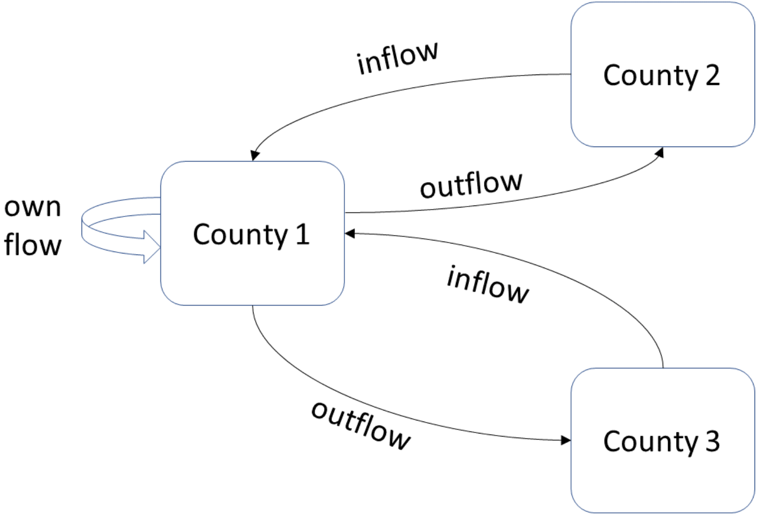
Employment changes, May 2020 vs February 2020



Strategy

- Exploit variation of lockdowns' start-end dates + commuting flows
  - "Own county"
  - Neighbouring counties
- Estimate effect on employment (and unemployment)
- Causal relationship: IV strategy
- Mechanism: consumers and POI-level employment (proxy)

Mechanism


inflow
County 2
outflow
own
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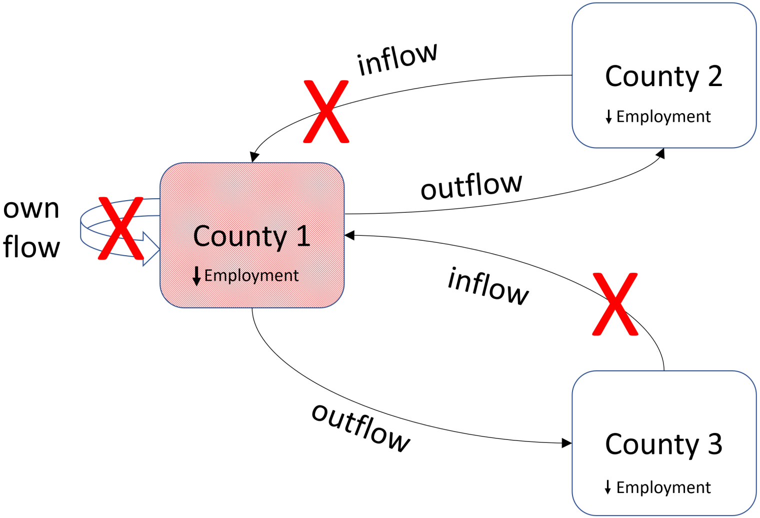

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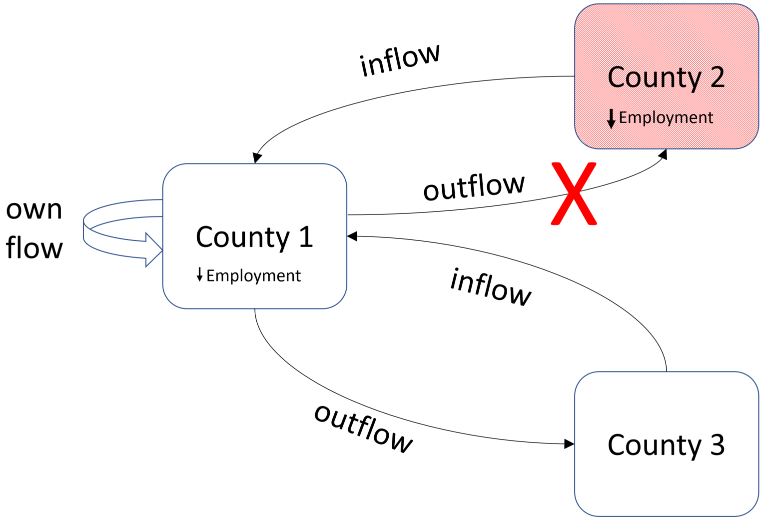

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What We Find

- **Lockdown effects:** $\approx 50 - 60\%$ **of unemployment, employment change**

- Spillovers explain:
  - 15-25% of unemployment increase
  - 10-15% of employment fall

- Large heterogeneity across space

- Restaurants, retail individual POIs:
  1. If clients come from a different county
  2. $\implies$ Larger job losses when the neighbours go into "lockdown",

Outline

Outline

Literature

- Theoretical SIR-Economic models
  - Role of "contact" externalities (Chang et al., 2020)
  - Heterogeneous agents (Kaplan, Moll, Violante 2020)
- Empirical estimations of lockdown effects
  - Consumption (Goolsbee, Syverson 2020)
  - Unemployment (Baek et al., 2020)
  - Exploiting workforce exposed to lockdowns (Borri et al. 2020)
- Labour market spillovers: little to no mention
  - Mainly used in SIR-Economic model
  - Optimal lockdown policies (Fajgelbaum et al., 2020)

Outline

The effect of a lockdown

- We will use two measures of employment
  1. Residence-based: sum of all employed people who live in a county (possibly held in other counties)
  2. Workplace-based: sum of all jobs in a county (possibly held by residents of other counties)
- I will explain our methodology using the residence-based measure
- Will provide results for both

Total Employment

- $i = 1, \ldots, N$: "home" counties
- $i' = 1, \ldots, N$: neighbouring counties (i included)
- Workers can commute from i to any $i' \rightarrow E_{ii'}$: commuting flows from i to i'
- Total employment is:

$$E_i = \sum_{i'=1}^{N} E_{ii'}$$

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The effect of a lockdown

- $i = 1, \ldots, N$: "home" counties
- $i' = 1, \ldots, N$: neighbouring counties
  $\rightarrow E_{ii'j}$: commuting flows from i to i' in sector j
- $j = 1, \ldots, N$: lockdown counties
  $\rightarrow L_j$: lockdown status indicator for j
- $\nabla_X L_i dX_i$: non-lockdown terms

$$\Delta \frac{E_i}{\text{Pop}_i} \approx \sum_{j=1}^{N} \sum_{i'=1}^{N} \frac{\partial \frac{E_{ii'}}{\text{Pop}_i}}{\partial L_j} dL_j + \nabla_X \left(\frac{E_i}{\text{Pop}_i} \right) dX_i$$

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Infeasible for empirical strategy, need simplifying assumptions

The effect of a lockdown

We assume that:

1. Effects are continuous across all counties
   No "jumps" in consumption, work patterns
2. Network effects are negligible
3. Lockdowns affect each flow in the same proportion

The effect of a lockdown

We assume that:

1. Effects are continuous across all counties
2. Network effects are negligible
   County i' affects i only directly, not through i''
   Lockdown in i' affectes i through $E_{ii'}$

$$\frac{\partial \frac{E_{ii'}}{\mathrm{Pop}_i}}{\partial Lock_j} = 0 \;\; \forall j \neq i, i'$$

3. Lockdowns affect each flow in the same proportion

The effect of a lockdown

We assume that:

1. Effects are continuous across all counties
2. Network effects are negligible
3. Lockdowns affect each flow in the same proportion

$$\frac{1}{E_{ij}}\frac{\partial E_{ij}}{\partial L_j} = \frac{1}{E_{i'j'}}\frac{\partial E_{i'j'}}{\partial L_{j'}} \quad \forall i, i', j, j' \in C$$

Easy to relax, will provide results accounting for:

- "Own" lockdown vs "neighbours' lockdown"
- Accounting for differences in sector composition and types of restrictions

The effect of a lockdown

We assume that:

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2. Network effects are negligible
3. Lockdowns affect each flow in the same proportion

$$\Delta \frac{E_i}{\text{Pop}_i} \approx \underbrace{\frac{\partial \left(\frac{E_i}{\text{Pop}_i}\right)}{\partial L}}_{\text{Effect of lockdowns}} \times \underbrace{\left(\sum_{j \in C} \frac{E_{ij}}{\text{Pop}_i} \text{Lockdown}_j\right)}_{\text{Avg L exposure, wgt by flows}} + \nabla_X \left(\frac{E_i}{\text{Pop}_i}\right) dX_i$$

The effect of a lockdown

We assume that:

1. Effects are continuous across all counties
2. Network effects are negligible
3. Lockdowns affect each flow in the same proportion
4. Allow for different derivatives for own vs neighbours' lockdowns

$$\Delta \frac{E_i}{\text{Pop}_i} \approx \left(\frac{\partial \left(\frac{E_i}{\text{Pop}_i} \right)}{\partial \kappa^{\text{own}}} \kappa_i^{\text{own}} + \frac{\partial \left(\frac{E_i}{\text{Pop}_i} \right)}{\partial \kappa^{\text{neighbours}}} \kappa_i^{\text{neighbours}} \right) + \nabla_X \left(\frac{E_i}{\text{Pop}_i} \right) dX_i$$

Outline

Empirical Strategy

Run a regression of the form:

$$y_{ti} = \beta_0 + \beta_1 X_{ti} + I_c + I_t + \Theta_{it} + \varepsilon_{ti}$$

where:

- y_{ti}: unemployment to population ratio of county $c \in C$
- X_{ti}: vector of county-level controls
- I_i and I_t: county-by-calendar-month and time fixed-effects,
- Θ_{ci} is intensity of treatments (own and neighbours' lockdowns)

Treatment measure

$$\Theta_{it} = f_i(\underbrace{\vec{L}_t^R}_{\text{lockdown intensities}}, \underbrace{\vec{\text{flow}}}_{\text{flows of commuters}})$$

From our decomposition:

$$\Theta_{it} = \gamma_{\text{own}}\, \kappa_{it}^{\text{own}}(L_{\text{own}}^R, \text{flow}_{\text{own}}) + \gamma_{\text{neighbour}}\, \kappa_{it}^{\text{neighbour}}(L_{\text{neighbours}}^R, \text{flow}_{\text{neighbours}})$$

$\implies$ $\gamma_{\text{own}}, \gamma_{\text{neighbour}}$ can be estimated by OLS

Treatment measure

- flow_{ir}: number of individuals from county i who commute to work in county r
- Measures of lockdown spillover intensity:
  - Outflow based measure $\kappa_{ti}^{\text{outflow}} = \frac{\sum_{r \in C: r \neq i} L_{rt}^{R} * \text{flow}_{cr}}{\text{Population}_i}$

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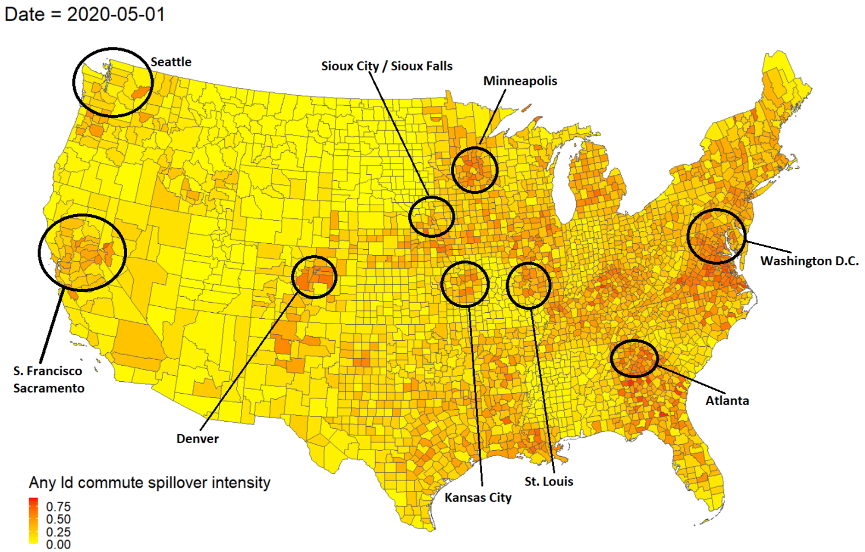
- Intensity of own lockdown

$$\kappa_{ti}^{\text{own}} = \frac{L_{it}^{R} * \text{flow}_{ii}}{\text{Population}_i}$$

An example: May 2020 spillover intensity (κ^{outflow})



Outline

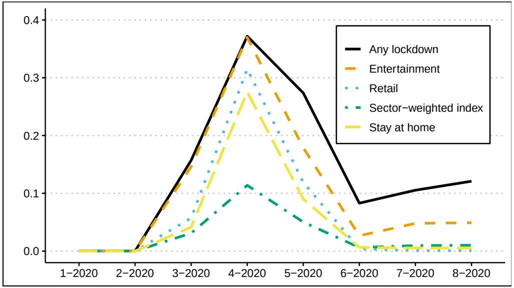
Data sources

- *Unemployment*: BLS county-level Local Area Unemployment Statistics
  Non-survey, county-level monthly estimates
- *Employment*: Quarterly Census of Employment and Wages
  Registers all workers who were reported for UI
- Rescale:
  - Unemployment $\rightarrow$ by working-age population
  - Employment $\rightarrow$ 2019 average level
- Commuting data: 2011 - 2015 ACS survey
- Consumers mobility, POI visits: Safegraph
- Own business restrictions database (cross-verified with other sources)

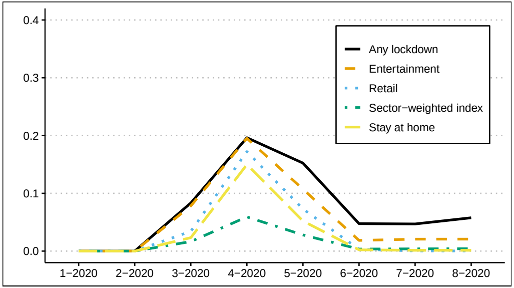
Types of lockdown orders

- We distinguish between four types of lockdown orders:
    1. Stay-at-home orders: all non-essential activities closed
    2. Retail closures: non-essential shops closed, but manifacturing open
    3. Restaurant closures
    4. Bars closures
- Ordinal relationship ($\implies$ bars closures = "any lockdown")

Timeline of lockdowns



(a) Own intensity



(b) Neighbour intensity

Figure 1: Indicators of own and neighbours' lockdown intensity, by restriction type

Outline

OLS estimates

	Unemployment/(working age population)					
	(1) No Spillovers	(2) No Spillovers Alt.	(3) Baseline	(4) Lags	(5) Exposure	(6) Exposure+Lags
Share of Month in Any Lockdown	0.0187***					
	(0.00281)					
Own Any lockdown		0.0417***	0.0326***	0.0228***	-0.0249*	-0.0292**
		(0.00850)	(0.00470)	(0.00490)	(0.0115)	(0.0108)
Any lockdown spillover			0.0204*	-0.00929	0.0288***	-0.00278
			(0.00961)	(0.00944)	(0.00784)	(0.00808)
L.Own Any lockdown				0.0430***		0.0306*
				(0.00473)		(0.0123)
L.Any lockdown spillover				0.0661***		0.0713***
				(0.0120)		(0.0117)
Own Any lockdown × Exposure					0.460***	0.408***
					(0.0925)	(0.0857)
L.Own Any lockdown × L.Exposure						0.128
						(0.106)
Constant	0.0299***	0.0300***	0.0300***	0.0286***	0.0302***	0.0287***
	(0.000210)	(0.000269)	(0.000835)	(0.000719)	(0.000865)	(0.000757)
Observations	133644	133644	133644	130536	129759	126741
R^2	0.876	0.878	0.884	0.891	0.890	0.899
Unemployment mean 02-2020	.025	.025	.025	.025	.025	.025
County and Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Exposure	No	No	No	No	Yes	Yes

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IV Strategy

- What if the county-level decision to go into lockdown is endogenous?
  - Local politicians choose lockdown according to state of the economy
  - A county's economy is "pivotal" for the state

- Instrument the spillover measure with the one calculated using:
  - Flow from counties **not** in the same state
  - **Proxied** by their state-wide lockdown status

- Exclusion assumption: neighbouring states' decision affect county i's outcomes *only* through the lockdown status of the counties it commutes with

IV variable calculation

- Instrumented variable:

$$\kappa_{ti}^{\text{outflow}} = \frac{\sum_{r \in C: r \neq i} L_{tr}^{R} * \text{flow}_{ir}}{\text{Population}_i}$$

C' is the set of commuting destination counties which are not in the same state
L^S is the state-wide lockdown indicator for county r

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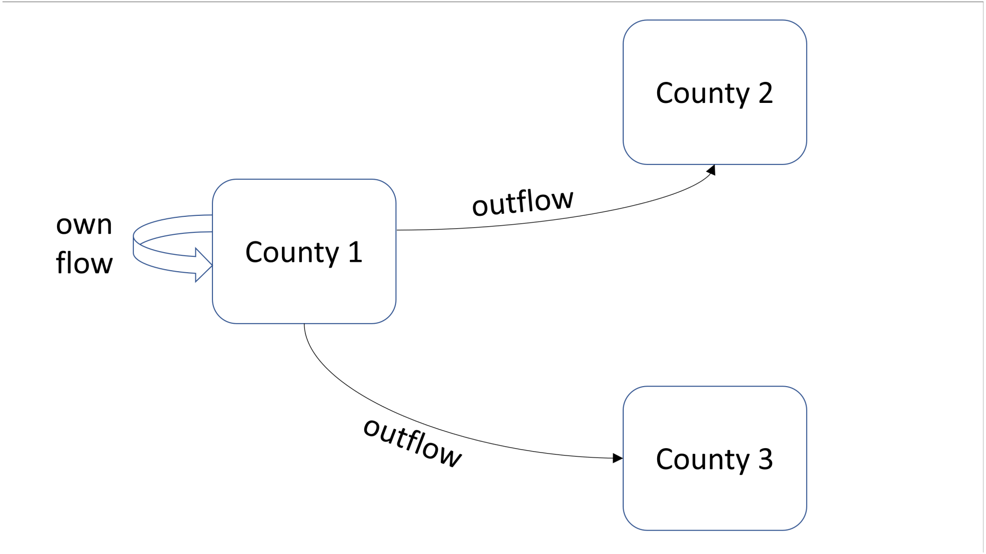
$$\kappa_{ti}^{\text{outflow}} = \frac{\sum_{r \in C: r \neq i} L_{tr}^{R} * \text{flow}_{ir}}{\text{Population}_i}$$

- Instrument:

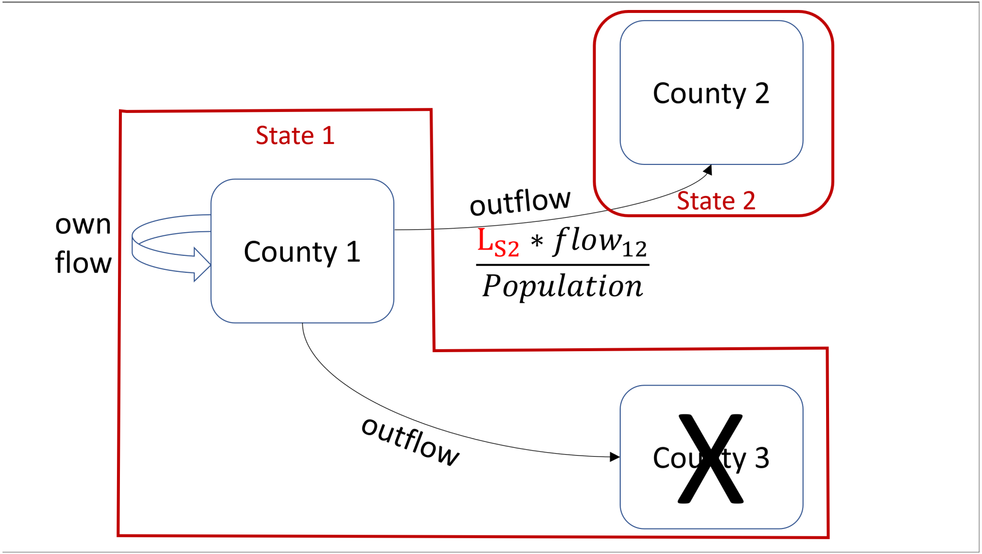
$$\kappa_{ti}^{\text{iv, outflow}} = \frac{\sum_{r \in C'} L_{tr}^{S} * \text{flow}_{ir}}{\text{Population}_i} \Big/ \frac{\sum_{r \in C'} \text{flow}_{ir}}{\sum_{r \in C: r \neq i} \text{flow}_{ir}}$$

C' is the set of commuting destination counties which are not in the same state
L^S is the state-wide lockdown indicator for county r

IV



IV


County 2
State 1
State 2
outflow
own
flow
County 1
$\frac{L_{S2} * flow_{12}}{Population}$
outflow
County 3
X

IV estimates (Unemployment)

	Unemployment/(working age population)					
	(1) No Spillovers	(2) No Spillovers Alt.	(3) Baseline	(4) Lags	(5) Exposure	(6) Exposure+Lags
Share of Month in Any Lockdown	0.0187***					
	(0.00281)					
Own Any lockdown		0.0417***	0.0327***	0.0220***	-0.0276*	-0.0316**
		(0.00850)	(0.00470)	(0.00445)	(0.0112)	(0.0104)
Any lockdown spillover			0.0405**	0.00356	0.0499***	0.00867
			(0.0126)	(0.00887)	(0.0109)	(0.00774)
L.Any lockdown spillover				0.0721***		0.0804***
				(0.00942)		(0.00909)
L.Own Any lockdown				0.0466***		0.0337**
				(0.00526)		(0.0125)
Own Any lockdown $\times$ Exposure					0.484***	0.423***
					(0.0919)	(0.0866)
L.Own Any lockdown $\times$ L.Exposure						0.134
						(0.106)
Observations	133644	133644	133644	130536	129759	126741
R^2	0.876	0.878	0.107	0.168	0.154	0.226
Kleinberg-Paap F-stat			3944.17	1389.93	3884.22	1319.95
Unemployment mean 02-2020	.025	.025	.025	.025	.025	.025
County and Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Exposure	No	No	No	No	Yes	Yes

IV estimates (Unemployment)

	Unemployment/(working age population)					
	(1) **No Spillovers**	(2) No Spillovers Alt.	(3) Baseline	(4) Lags	(5) Exposure	(6) Exposure+Lags
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Covid controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Exposure	No	No	No	No	Yes	Yes

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Unemployment mean 02-2020	.025	.025	.025	.025	.025	.025
County and Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Exposure	No	No	No	No	Yes	Yes

IV estimates (Unemployment)

	Unemployment/(working age population)					
	(1) No Spillovers	(2) No Spillovers Alt.	(3) **Baseline**	(4) Lags	(5) Exposure	(6) Exposure+Lags
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	(0.00281)					
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Unemployment mean 02-2020	.025	.025	.025	.025	.025	.025
County and Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Exposure	No	No	No	No	Yes	Yes

Sector-weighted lockdown index (Unemployment)

	Unemployment/(working age population)					
	(1)	(2)	(3)	(4)	(5)	(6)
	No Spillovers	Baseline	Lags	IV (rescaled)	IV (non-rescaled)	IV (Lags, res)
Own lockdown	0.184***	0.188***	0.135***	0.191***	0.190***	0.135***
	(0.0202)	(0.0198)	(0.0183)	(0.0200)	(0.0195)	(0.0177)
Lockdown spillover		0.149***	0.0536*	0.252***	0.189*	0.103***
		(0.0322)	(0.0263)	(0.0343)	(0.0923)	(0.0238)
L.Own lockdown			0.171***			0.183***
			(0.0162)			(0.0169)
L.Lockdown spillover			0.252***			0.346***
			(0.0350)			(0.0412)
Constant	0.0293***	0.0285***	0.0273***			
	(0.000959)	(0.000919)	(0.000852)			
Observations	126549	126549	123606	126549	126549	123606
R^2	0.892	0.894	0.904	0.178	0.184	0.252
Kleinberg-Paap F-stat				3334.49	127.84	1498.06
Unemployment mean 02-2020	.025	.025	.025	.025	.025	.025
CountyxMonth and Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Exposure	Yes	Yes	Yes	Yes	Yes	Yes

Sector-weighted lockdown index (Unemployment)

	Unemployment/(working age population)					
	(1) No Spillovers	(2) **Baseline**	(3) Lags	(4) IV (rescaled)	(5) IV (non-rescaled)	(6) IV (Lags, res)
Own lockdown	0.184***	**0.188*****	0.135***	0.191***	0.190***	0.135***
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CountyxMonth and Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Exposure	Yes	Yes	Yes	Yes	Yes	Yes

Sector-weighted lockdown index (Unemployment)

	Unemployment/(working age population)					
	(1) No Spillovers	(2) Baseline	(3) Lags	(4) **IV (rescaled)**	(5) **IV (non-rescaled)**	(6) IV (Lags, res)
Own lockdown	0.184***	0.188***	0.135***	0.191***	0.190***	0.135***
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Unemployment mean 02-2020	.025	.025	.025	.025	.025	.025
CountyxMonth and Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Exposure	Yes	Yes	Yes	Yes	Yes	Yes

Workplace-based Employment and Consumption flows

	Establishment-based Employment index (1 = 2019 employment)				
	(1) No Spillovers	(2) Baseline	(3) Lags	(4) IV (rescaled)	(5) IV (non-rescaled)
Own lockdown intensity	-0.253***	-0.226***	-0.163***	-0.222***	-0.151***
	(0.0189)	(0.0238)	(0.0194)	(0.0244)	(0.0339)
Lockdown spillover		-0.230	-0.284**	-0.433**	-1.526***
		(0.139)	(0.102)	(0.152)	(0.316)
Entertainment Lockdown Consumption Spillover		-0.358***	-0.0231	-0.393***	-0.315*
		(0.0846)	(0.109)	(0.115)	(0.129)
Ent. Lockdown Cons. Spillover × share month in ent. order		0.246*	-0.0569	0.332*	0.369*
		(0.114)	(0.139)	(0.131)	(0.150)
L.Own lockdown intensity			-0.115***		
			(0.0203)		
L.Lockdown spillover			0.0193		
			(0.0855)		
L.Entertainment Lockdown Consumption Spillover			0.0966		
			(0.111)		
L.Ent. Lockdown Cons. Spillover × L.share month in ent. order			-0.218		
			(0.116)		
Constant	0.983***	0.984***	0.985***		
	(0.000881)	(0.00105)	(0.00105)		
Observations	123606	123606	120663	123606	123606
R^2	0.815	0.817	0.824	0.081	0.024
Kleinberg-Paap F-stat				869.96	41.2
Unemployment mean 02-2020	.025	.025	.025	.025	.025
CountyxMonth and Time FEs	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes
Industry Exposure	Yes	Yes	Yes	Yes	Yes

Workplace-based Employment and Consumption flows

	Establishment-based Employment index (1 = 2019 employment)				
	(1)	(2)	(3)	(4)	(5)
	No Spillovers	**Baseline**	Lags	IV (rescaled)	IV (non-rescaled)
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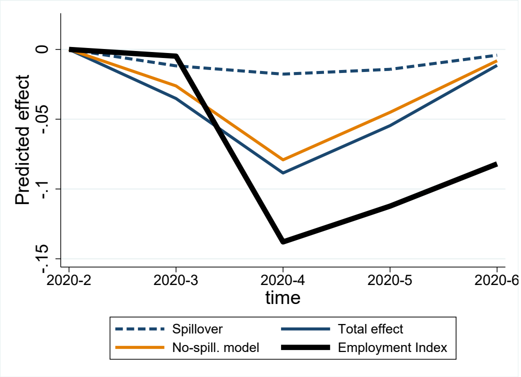
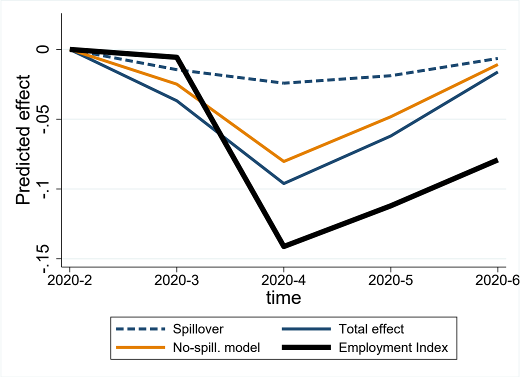
Unemployment mean 02-2020	.025	.025	.025	.025	.025
CountyxMonth and Time FEs	Yes	Yes	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes	Yes	Yes
Industry Exposure	Yes	Yes	Yes	Yes	Yes

Accounting for spillovers: average effects (Employment)

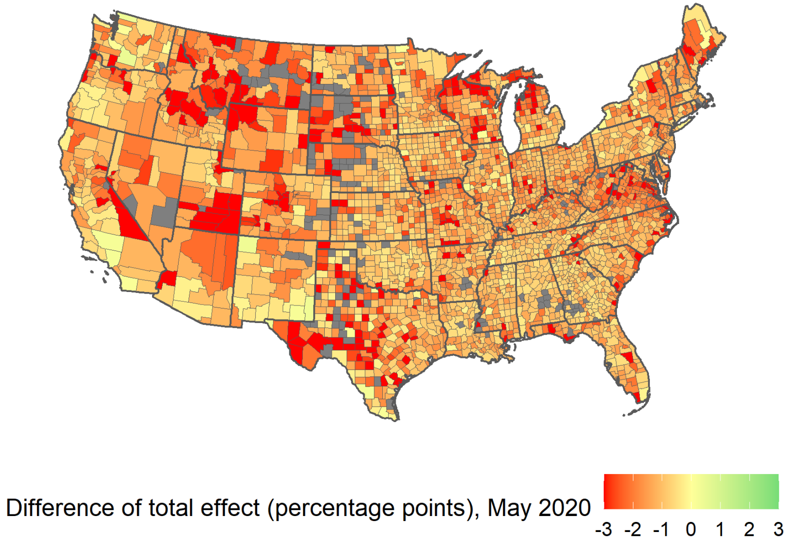


(a) All counties



(b) Above-median commuting

Accounting for spillovers: spatial effects (Employment)



Outline

Mechanism

- Spillovers are relevant (both as covariates and causally)

- Employment affected by:
  - Commuting spillovers (es: you lose your job, do not consume at home)
  - Consumption spillovers (es: consumers cannot move between counties anymore)

Now: Evidence for a consumption spillover mechanism

Mechanism

- Spillovers are relevant (both as covariates and causally)

- Employment affected by:
  - Commuting spillovers (es: you lose your job, do not consume at home)
  - Consumption spillovers (es: consumers cannot move between counties anymore)

Now: Evidence for a consumption spillover mechanism

Mobility Data

- Safegraph: mobile phones' pings + **highly detailed geometry** of shops
- Provides detailed weekly data on visits
  - We know where consumers of each shop come from (Census Block)
  - **Use "long visits" (≥4 hours) as proxy for employment**
    High correlation (0.76) with QCEW county-level employment in 2020
- Matches geometry to 4-digits NAICS
  - Build closed/open daily variable for each shop
  - Drop sectors where consumers stay long times (hotels, sport venues, ...)

Mobility Data

- We can build:
  1. Outcome: footfall-based employment proxy
  2. Treatment: neighbours/local county is open/close (by sector)
  3. Weights: share of visits coming from people residing in each neighbour

Mechanism

Are neighbours' policies affecting the most shops highly exposed to neighbours' visits?

Empirical Strategy

Run a regression of the form:

$$y_{tij} = \beta_0 + \beta_1 X_{tj} + I_{ij} + I_t + \Theta_{cij} + \varepsilon_{tij}$$

where:

- y_{tij}: foot-fall employment proxy (shop level)
- X_{tj}: county-level controls
- I_{ij} and I_t: POI and week fixed-effects,
- Θ_{tij} intensity of treatment

Empirical Strategy

Run a regression of the form:

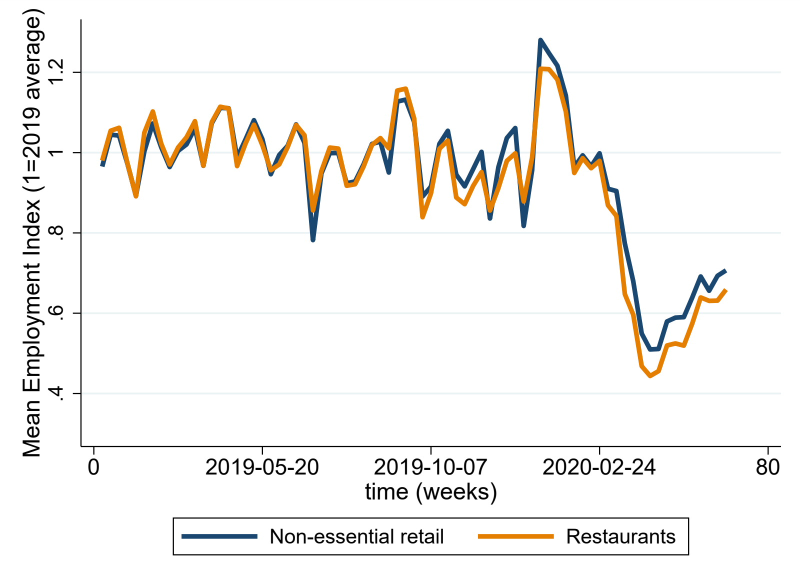
$$y_{tij} = \beta_0 + \beta_1 X_{tj} + I_{ij} + I_t + \Theta_{cij} + \varepsilon_{tij}$$

where:

- y_{tij}: foot-fall employment proxy (shop level)
- X_{tj}: county-level controls
- I_{ij} and I_t: POI and week fixed-effects,
- Θ_{tij} intensity of treatment

$\Theta_{tij} = \gamma_1(\text{Share of week closed})_{tij} + \gamma_2(\text{Share of visitors from neigh. under lockdown})_{tij}$

Employment proxy, by week



OLS results - Restaurants (1 = 100% of 2019 employment)

	Long visits index (1 = avg 2019), Restaurants		
	(1) Baseline	(2) Baseline + SAH	(3) Mobility Limitation
Closed Sector	-0.144***	-0.137***	-0.149***
	(0.0157)	(0.0154)	(0.0152)
Neighbours' restaurants closures	-0.446***	-0.523***	-0.499***
	(0.103)	(0.107)	(0.107)
Closed Sector × Neighbours' restaurants closures	0.0361	0.125	0.177
	(0.108)	(0.105)	(0.103)
Own SAH order		-0.0926***	-0.0716***
		(0.0127)	(0.0162)
Neighbours' SAH closures			-0.118***
			(0.0343)
Constant	0.976***	0.983***	0.983***
	(0.00586)	(0.00501)	(0.00497)
Observations	27064950	27064950	27064950
R^2	0.113	0.114	0.114
POI FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes

OLS results - Restaurants ($1 = 100\%$ of 2019 employment)

	Long visits index ($1 =$ avg 2019), Restaurants		
	(1) **Baseline**	(2) Baseline + SAH	(3) Mobility Limitation
Closed Sector	-0.144***	-0.137***	-0.149***
	(0.0157)	(0.0154)	(0.0152)
Neighbours' restaurants closures	**-0.446******	-0.523***	-0.499***
(=1 if all 2019 visits are from closed neighbours)	(0.103)	(0.107)	(0.107)
Closed Sector × Neighbours' restaurants closures	0.0361	0.125	0.177
	(0.108)	(0.105)	(0.103)
Own SAH order		-0.0926***	-0.0716***
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Constant	0.976***	0.983***	0.983***
	(0.00586)	(0.00501)	(0.00497)
Observations	27064950	27064950	27064950
R^2	0.113	0.114	0.114
POI FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes

IV results - Restaurants

	Long visits index (1 = avg 2019), Restaurants		
	(1)	(2)	(3)
	Baseline	Baseline + SAH	Open + SAH
Neighbours' restaurants closures	-0.512***	-0.589***	-0.505***
	(0.134)	(0.139)	(0.145)
Closed Sector × Neighbours' restaurants closures	-0.0471	0.0290	0.160
	(0.131)	(0.134)	(0.148)
Closed Sector	-0.121***	-0.113***	-0.148***
	(0.0178)	(0.0172)	(0.0256)
Own SAH order		-0.0879***	-0.0374
		(0.0120)	(0.0217)
Neighbours' SAH closures			-0.287*
			(0.119)
Observations	27064950	27064950	27064950
R^2	0.003	0.004	0.004
Kleinberg-Paap F-stat	76.31	75.68	12.81
POI FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Covid controls	Yes	Yes	Yes

Conclusions

- Lockdowns have spatial externalities due to economic interconnections
- They account for:
  1. 1/3rd of lockdown effects (mean) = 15% of total employment fall
  2. 1/2 to 3/4 in counties highly exposed to commuting
  3. $\implies$ naive estimates are quantitatively + spatially biased
- Provided high-frequency, granular evidence for a consumption-based mechanism
- Policy: "lockdown grants" should account for indirectly affected businesses

Thank You!