Non-Pharmaceutical Interventions, Teleworkability, and Involuntary Job Separations

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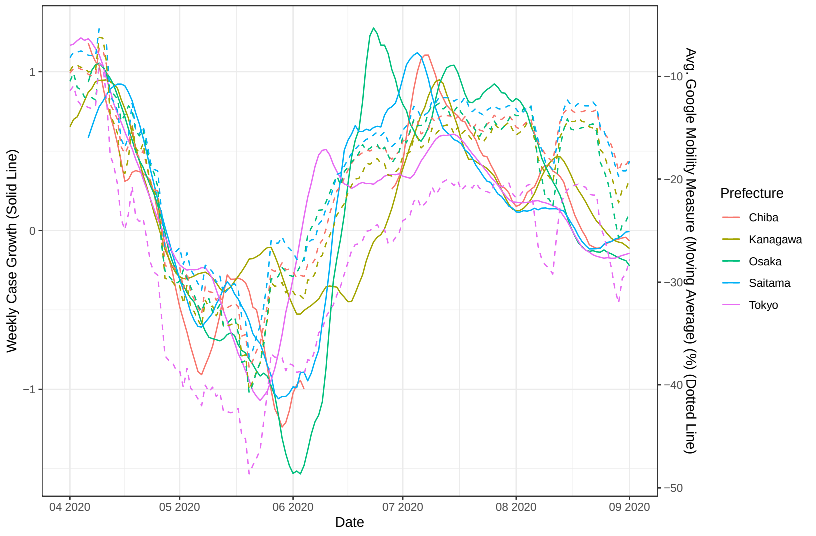
[a]The views expressed in this paper are those of the authors and do not necessarily represent the official views of the Economic and Social Research Institute, the Cabinet Office, the Government of Japan or the institutions the authors are affiliated with.

Issues

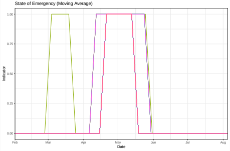
- What is the impact of the "lockdown" policies and people's movement on job losses and the spread of COVID-19 in Japan?
- The role of teleworkablity?
- What is a trade-off between job losses and the spread of COVID-19?

Case Growth and Mobility

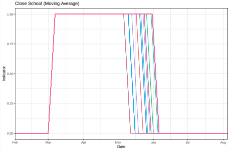


Prefecture Government Policies in Japan

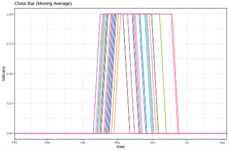
State of Emergency



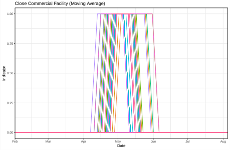
School Closure



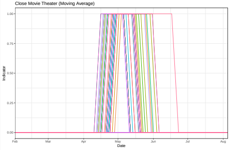
Bar Closures



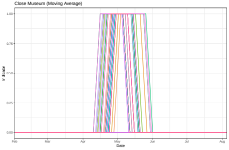
Commercial Closure



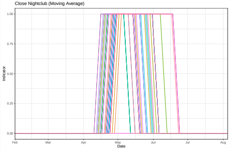
Movie Closure



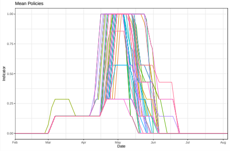
Museum Closure



Nightclub Closure

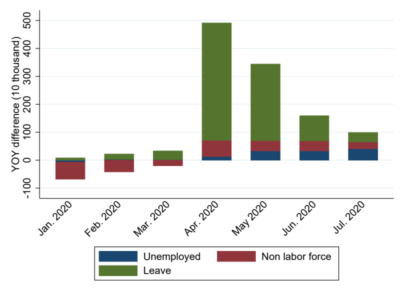


Policy Index

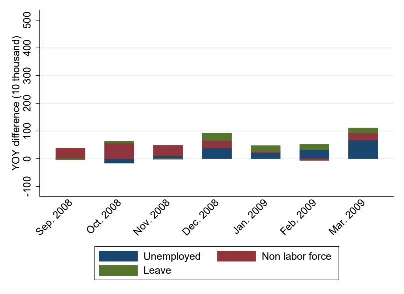


YOY difference in unemployed, non-labor force, leave

COVID-19



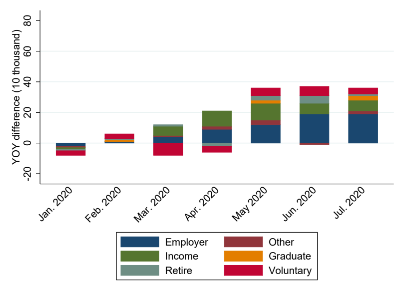
Great Recession



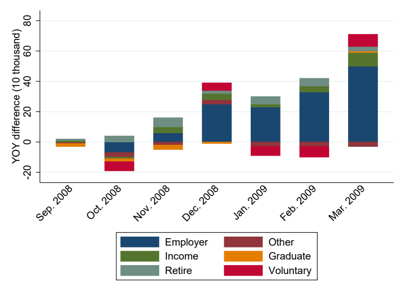
Source: Labor Force Survey

YOY difference in involuntary job separations

COVID-19

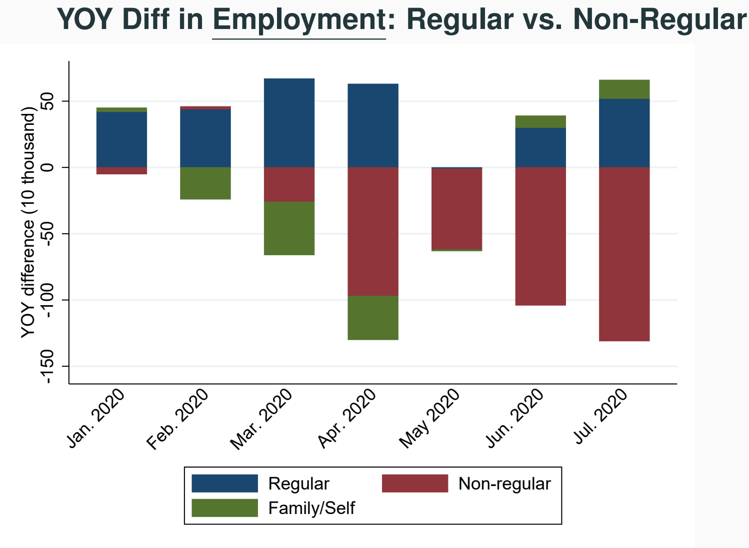


Great Recession



Source: Labor Force Survey

YOY difference in employment: regular vs. non-regular



Source: Labor Force Survey

What is the impact of the “lockdown” policies and people’s movement on job losses?

Did policies and voluntary restraint lead to job losses?

$$\ln\left(\frac{Y_{i,j,2020}}{Y_{i,j,2019}}\right) = \beta_1 Z_{i,j} + \beta_2 Z_{i,j} \times Tel_i + \gamma Tel_i + X_i'\alpha + \epsilon_{ij}$$

for prefecture i on month $j = 2, 3..., 7$.

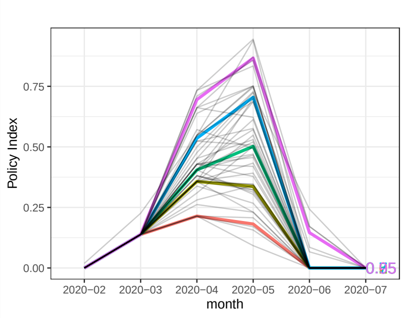
- $Y_{i,j}$: The number of job losses due to employer
- $Z_{i,j}$: Policy index or Mobility index
- Tel_i : Teleworkability index
- X_i : the log of GDP per capita, poverty rate, elderly rate, and population density

Prefecture-level Monthly Panel Data

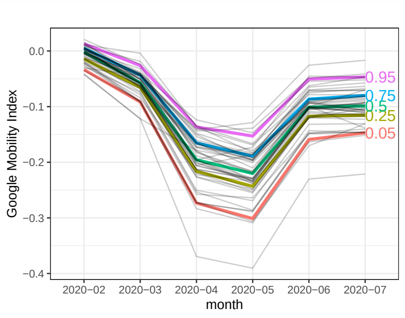
- Monthly panel data from Feb to July of 2020.
- “Involuntary job separations due to employer” from Monthly Report on Employment Insurance Programs, MHLW (Koyou-Hoken-Jigyou-Geppou)
- Policy Index = Average of 7 policy dummy variables
- Mobility Index = (Workplaces+Retail+Grocery+Transit)/4

Policy Index and Google Mobility Index

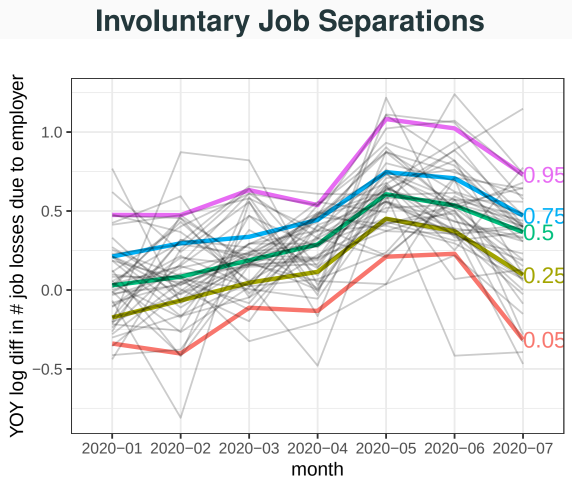
Policy Index



Google Mobility Index



Involuntary Job Separations

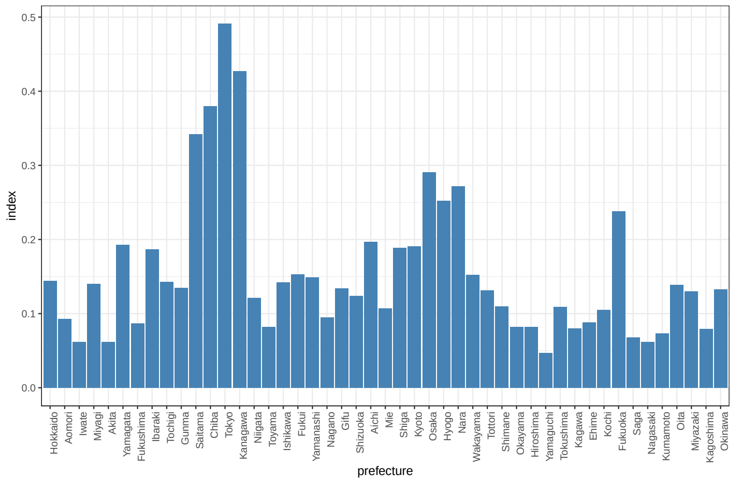


Teleworkability

Four different teleworkabilty indexes:

1. Indexes based on occupational task descriptions
    - Dingel-Neiman's measure mapped into Japanese occupational classifications.
    - DN's measure based on JONET.
2. Indexes based on actual telework hours data
    - Persol (April 12-13 2020, regular workers only).
    - Line (April 10-12 2020, office workers only).

Persol Teleworkability



Did policies and voluntary restraint lead to job loss?

	Dependent variable: Involuntary Job Separations			
	(1)	(2)	(3)	(4)
$Mobility_{i,j}$	-0.775^{*}	-2.719^{**}		
	(0.460)	(1.079)		
$Policy_{i,j}$			0.174	0.579^{**}
			(0.120)	(0.292)
$Persol_i$	-0.556^{**}	-0.233	-0.504^{**}	-0.375
	(0.277)	(0.257)	(0.257)	(0.247)
$Mobility_{i,j} \times Persol_i$		3.143^{***}		
		(1.205)		
$Policy_{i,j} \times Persol_i$				-0.842^{*}
				(0.469)
Observations	282	282	282	282
R^2	0.485	0.497	0.485	0.494

Note: Weighted by Population; Includes prefecture controls and month dummies.

Different teleworkability measures

	Line	DN	DN-JONET	Line	DN	DN-JONET
	Dependent variable: Involuntary Job Separations					
	(1)	(2)	(3)	(4)	(5)	(6)
$Mobility_{i,j}$	-2.743^{**}	-7.192^{***}	-3.972^{*}			
	(1.098)	(2.493)	(2.069)			
$Policy_{i,j}$				0.507^{*}	1.606^{**}	0.898^{*}
				(0.278)	(0.675)	(0.535)
Tel_i	-0.283	-0.751	-0.024	-0.381^{*}	-1.679	-0.284
	(0.234)	(1.395)	(1.049)	(0.225)	(1.234)	(0.972)
$Mobility_{i,j} \times Tel_i$	2.761^{**}	21.260^{***}	8.468^{**}			
	(1.109)	(7.373)	(4.226)			
$Policy_{i,j} \times Tel_i$				-0.676	-5.271^{**}	-2.190^{*}
				(0.417)	(2.273)	(1.278)
Observations	282	282	282	282	282	282
R^2	0.501	0.499	0.479	0.496	0.493	0.478

Note: Weighted by Population; Includes prefecture controls and month dummies.

IV regression — use Policy as an IV for Mobility

	Dependent variable: Involuntary Job Separations			
	Persol	Line	DN	DN-JONET
	(1)	(2)	(3)	(4)
$Mobility_{i,j}$	-7.384^{**}	-6.568^{*}	-10.896^{**}	-8.723
	(3.730)	(3.621)	(4.351)	(5.651)
$Mobility_{i,j} \times Tel_i$	7.182^{**}	5.724^{*}	31.196^{***}	16.356^{*}
	(3.446)	(3.004)	(11.662)	(9.714)
Tel_i	-0.163	-0.262	-0.196	-0.188
	(0.260)	(0.217)	(1.250)	(1.006)
Observations	282	282	282	282
R^2	0.451	0.468	0.493	0.462

Weighted by Population; Includes prefecture controls and month dummies.

Summary of Involuntary Job Loss Regression

- “Lockdown” Policies, Mobility $\downarrow$

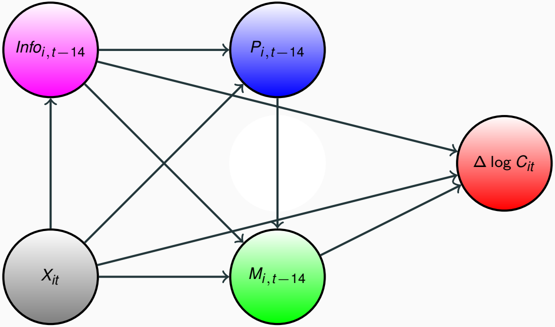
  $\Rightarrow$ Involuntary Job Separations $\uparrow$.

- Higher teleworkability weakens these relationships.

  (e.g., Tokyo suffers less from the state of emergency than other prefectures).

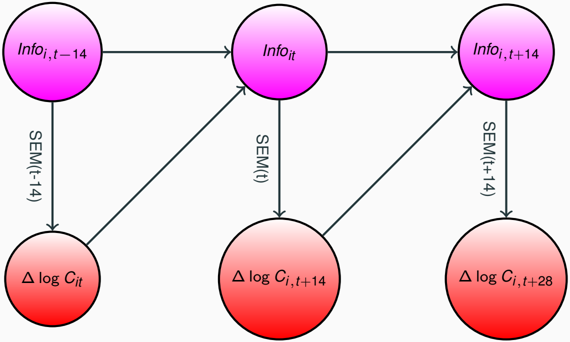
What is the impact of the “lockdown” policies and people’s movement on the spread of COVID-19?

Causal Diagram: Chernozhukov, Kasahara, and Schrimpf (2020)



- $\Delta \log C_{it}$: the growth rate of cases
- $P_{i,t-14}$: the lagged policies (e.g., state of emergency)
- $M_{i,t-14}$: the lagged behavior variables (Google mobility)
- $Info_{i,t-14}$: past cases
- X_{it}: confounders (prefecture characteristics, month dummies)

Dynamic feedback



$$
\begin{aligned}
Info_{i,t-14} &= \left(\Delta \log C_{i,t-14}, \log C_{i,t-14}\right)' \\
&= (\text{lagged case growth, lagged cases})
\end{aligned}
$$

Case Growth Regression Analysis

$$\Delta \log C_{it} = \alpha \mathrm{M}_{i,t-14} + \mu' \mathit{Info}_{i,t-14} + \delta_Y' X_{it} + \varepsilon_{it}^{y}$$

$$\mathrm{M}_{i,t-14} = \beta \mathrm{P}_{i,t-14} + \gamma' \mathit{Info}_{i,t-14} + \delta_B' X_{it} + \varepsilon_{it}^{b}$$

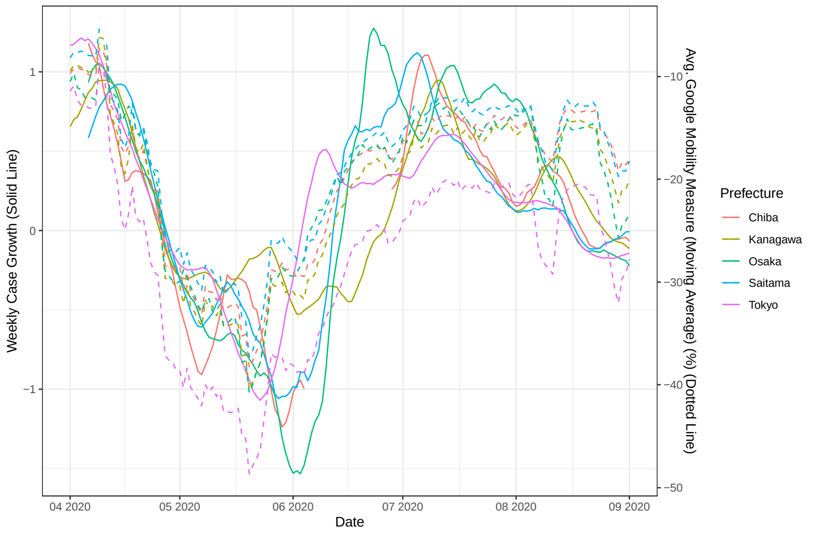
- $\Delta log \Delta C_{it}$: the growth rate of cases
- $\mathrm{M}_{i,t-14}$: Mobility Index lagged by 14 days
- $\mathrm{P}_{i,t-14}$: Policy Index lagged by 14 days
- $\mathit{Info}_{i,t-14}$: the log of lagged cases, lagged case growth
- X_{it}: prefecture-level characteristics and month dummies.

Daily Panel Data for COVID-19

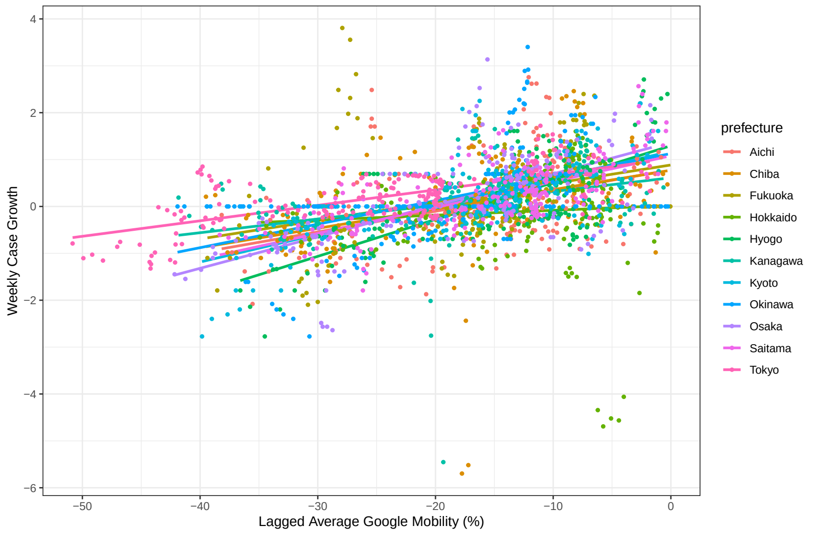
- Data Period: from March 29 to August 31.
- Daily cases: https://gis.jag-japan.com/covid19jp/
- The number of tests: Toyo Keizai
- Policy Index = Average of 7 policy variables
- Mobility Index = (Workplaces+Retail+Grocery+Transit)/4

We use 7 days moving averages of all variables

Case Growth and Mobility



Case growth and mobility



The Effect of Mobility and Information on Cases

	Dependent variable.: $\Delta log \Delta C_{it}$
Mobility	1.213**
	(0.478)
$\Delta log \Delta C_{i,t-14}$	0.131***
	(0.043)
$log \Delta C_{i,t-14}$	-0.244***
	(0.047)
Observations	2,270
R^2	0.426

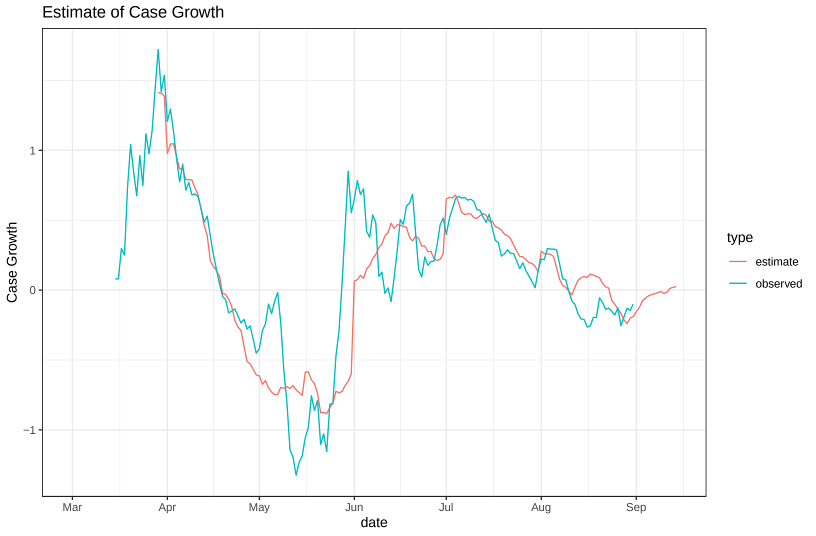
Note: Weighted by Population; prefecture controls, monthly dummies, Golden week dummy, and the log of test included.

The Effect of Policy on Mobility

	Dependent variable: $Mobility_{it}$	
	(1)	(2)
$Policy_{it}$	-0.144^{***}	-0.085^{***}
	(0.007)	(0.012)
Teleworkability		-0.272^{*}
		(0.141)
$Policy_{it} \times Teleworkability_i$		-0.194^{***}
		(0.031)
$\Delta log \Delta C_{it}$	0.013^{***}	0.012^{***}
	(0.002)	(0.002)
$log \Delta C_{it}$	-0.011^{***}	-0.008^{***}
	(0.001)	(0.001)
Observations	2,480	2,480
R^2	0.927	0.931

Note: Weighted by Population; prefecture controls, monthly dummies, and Golden week dummy included.

Fit and Prediction of Weekly Case Growth in Tokyo



Trade-off between job losses and the spread of COVID-19?

People's movement as an input for production function

The production function:

$$Y_t = \min\{L_t, \varphi(M_t)\},$$

$$\Rightarrow \quad Y_t = L_t = \varphi(M_t),$$

where

- L_t: employment
- M_t: people's movement
- $\varphi'(M_t)$ captures teleworkability.

Social planner's problem with SIRD model

$$
\begin{aligned}
v_0 = \max_{\{L_t\}} \sum_{t=0}^{\infty} \delta^t (1 - D_t) u(y_t) \\
\text{s.t.} \quad & y_t := \frac{L_t}{1 - D_t}, \quad M_t = \varphi^{-1}(L_t), \\
& S_{t+1} = S_t - \beta_t(M_t) S_t I_t && \text{(Susceptible)} \\
& I_{t+1} = (1 - \gamma) I_t + \beta_t(M_t) S_t I_t && \text{(Infectious)} \\
& R_{t+1} = R_t + \pi_r I_{t+1} && \text{(Recoverd)} \\
& D_{t+1} = D_t + \pi_d I_{t+1} && \text{(Dead)}
\end{aligned}
$$

Trade-off between jobs and deaths

$$L_t \uparrow \;\Rightarrow\; M_t \uparrow \;\Rightarrow\; I_{t+1} \uparrow \;\Rightarrow\; D_{t+1} \uparrow$$

Optimality condition:

$$v_t(S_t, I_t, D_t) = \max_{L_t} (1 - D_t)u(y_t) + \delta v_{t+1}(S_{t+1}, I_{t+1}, D_{t+1}),$$

$\Rightarrow$

$$u'(y_t) = \quad \delta \left(\frac{\partial v_{t+1}}{\partial I_{t+1}} - \frac{\partial v_{t+1}}{\partial S_{t+1}} + \pi_d \frac{\partial v_{t+1}}{\partial D_{t+1}} \right) \frac{\partial I_{t+1}}{\partial L_t}$$

where

$$\frac{\partial v_{t+1}}{\partial I_{t+1}} < 0, \quad \text{infectious} \uparrow \Rightarrow \text{future infections/deaths} \uparrow$$

$$-\frac{\partial v_{t+1}}{\partial S_{t+1}} > 0, \quad \text{susceptible} \downarrow \Rightarrow \text{future infections} \downarrow$$

$$\pi_d \frac{\partial v_{t+1}}{\partial D_{t+1}} < 0, \quad \text{disutility from deaths.}$$

Motivations for Regression Analysis

- Case Growth Regression:

$$\frac{I_{t+1} - I_t}{I_t} = -\gamma + \beta_t(M_t),$$

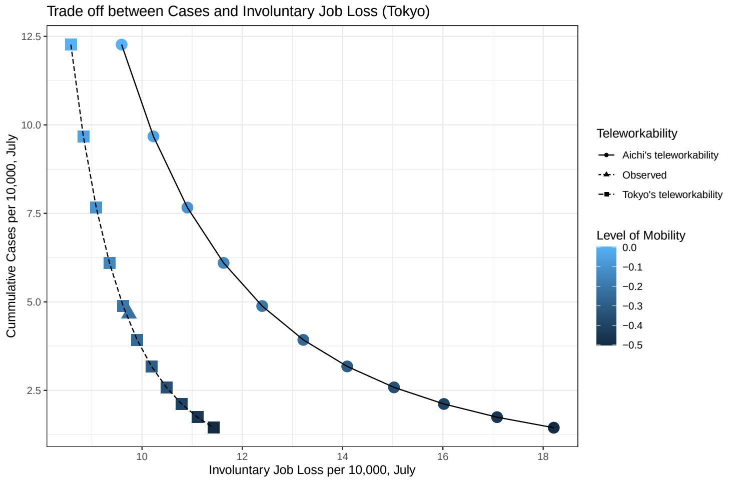
$$\Rightarrow \quad \Delta \log C_{it} = \alpha' \mathrm{M}_{i,t-14} + \mu' Inf_{i,t-14} + \delta_Y' X_{it} + \varepsilon_{it}^{y}$$

- Job Loss Regression:

$$1 - L_t = 1 - \varphi^{-1}(M_t).$$

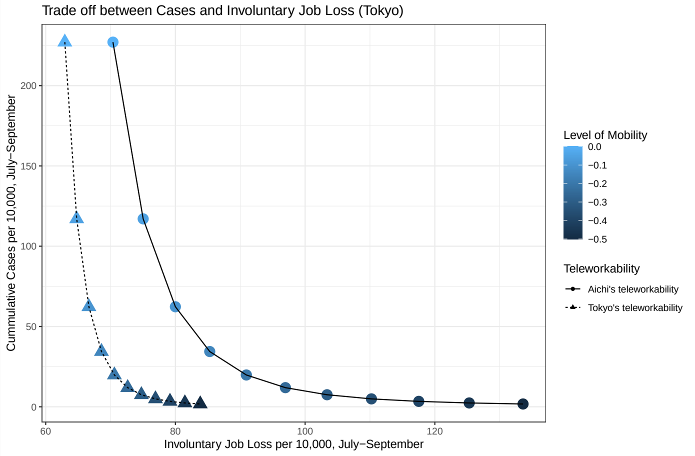
$$\Rightarrow \quad \ln\left(\frac{Y_{i,j2020}}{Y_{i,j,2019}}\right) = \beta_1 M_{i,j} + \beta_2 M_{i,j} \times Tel_i + \gamma Tel_i + X_i' \alpha + \epsilon_{ij}$$

Short-run trade off between job loss and infection in July



$$I_{t+1} = (1 - \gamma + \beta_t(\varphi^{-1}(L_t)))I_t \quad \text{given } I_t.$$

“Mid-run” trade off: July-September



$$\sum_{s=1}^{T} I_{t+s} = \sum_{s=1}^{T} (1 - \gamma + \beta_{t-1+s}(\varphi^{-1}(L_{t-1+s})))^{s} I_t.$$

Discussion

- Short-run trade-off in July in Tokyo:
  - The short-run trade-off is

    $\rightarrow$ saving 1 job loss requires 7 more cases.
  - What if Tokyo is like Aichi?

    $\rightarrow$ saving 1 job loss requires 1 more case.
- Mid-run trade-off in July-Sept:

  $\rightarrow$ saving 1 job loss requires 25 more cases.
- Keeping low job losses for a longer period requires a larger number of cumulative cases because of “exponential growth”.

Conclusion

- "Lockdown" policies $\Rightarrow$ Mobility $\downarrow$.
- Mobility $\downarrow$ $\Rightarrow$ Involuntary Job Loss $\uparrow$ and Case Growth $\downarrow$.
- **High teleworkability** weakens these relationships.

  (e.g., Tokyo suffers less from the state of emergency).
- Quantifying short-run vs. long-run trade-off between infections and job losses.

Limitations and caveats

- Limited economic outcomes.
- Limited health outcomes.
- Google mobility measures are useful but limited.
- Trade-offs are different across different individuals.
  - Job loss risk depends on regular vs. non-regular, occupations/industries.
  - Health risk depends on young vs. old, underlying medical conditions.

  $\Rightarrow$ Negative externality under heterogenous risks.