Epidemiological and Economic Effects of Lockdown

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Background – Shutting down

**Contact rate**

**Employment**

Percent change from March 1st

March 01 | April 01 | May 01 | June 01

March 01 | April 01 | May 01 | June 01
Background – Non-pharmaceutical interventions (NPIs)
Summary

Mostly voluntary action, not government mandates. NPIs explain:
• 7% of the fall in the contact rate,
• 15% of the fall in employment.

NPIs reduced confirmed COVID-19 deaths through May 31st by more than 33,000 – or 29% – and reduced employment by almost 3 million – or 1.7%.

Issuing stay-at-home orders and closing schools earlier – without ordering businesses to close – could have saved more lives and one million jobs.
Methods

Infectious disease model (SEIR) augmented with behavioral responses, simultaneous determination of epidemiological and economic outcomes.

New high-frequency measures of contact rates and employment at the county level, aggregating information from many proxies via principal components.

Difference-in-differences framework to estimate behavioral parameters, integrated directly into the model.
Augmented SEIR model

Disease transmission depends on contacts (physical proximity) between infectious and susceptible persons and the likelihood of infection per contact:

\[ \text{transmission rate} = \text{contact rate} \times \text{infection rate} \]

Conventional model: contact rate is externally given.

Augmented model: contact rate responds to severity of local epidemic and to NPIs. Employment depends on the same factors.
Augmented SEIR model

Three components of behavior determine contact rate and employment:

1. Response to local infection risk
2. Response to state and local NPIs
3. Precautionary response, by demographic/economic/political characteristics

Note: Precautionary response may include more than just pure “precaution” (e.g. effects of CDC guidance, national trends in non-modeled NPIs).
Data – COVID-19

Estimate true infections by estimating the "confirmation rate":

1. Confirmation rate = confirmed cases / (deaths / IFR)
2. Regress output from step 1) on the positivity rate and a time trend
3. Fit values from step 2) and use to scale confirmed cases

Estimate historical reproduction number using method from Cori et. al. (2013):

• Requires daily infection data and an assumption about the distribution of the virus’s *serial interval* (days between successive cases)
• Iterate over hundreds of combinations of serial interval parameters, choosing the set that best matches observed epidemic curve
Data – Contact rate and employment

Daily, county-level proxies from:

• mobile device location data
• business and financial services software
• payroll service providers
• web search activity

Sources: PlaceIQ, SafeGraph, Google Mobility, Unacast, Homebase, Opportunity Insights (Paychex, Intuit, Earnin, Kronos), Google Trends
Contact rate and employment indexes

Challenges:

• Many imperfect proxies for an unmeasured target.
• Daily data for small geographic units → lots of noise.
• Relationship between proxies and target varies by county.

Solution: principal components

• Extract a latent signal that explains common variation across all proxies.
• Removes idiosyncratic variation and noise.
• Weights on each proxy are county-specific.
Daily employment index vs. BLS monthly employment
Declines in contacts and employment were mostly voluntary action, not government mandates.
Decomposition of response to COVID-19

- Contact rate
- Employment

Log difference from March 1st

- State and local NPIs
- Local infection risk response
- Precautionary behavior
Precautionary contact rate response and political preference
Precautionary employment response and industry

Precautionary change in employment

Log difference from March 1st

Quartile of leisure and food services share

Mar | Apr | May | Jun

1

2

3

4

15
NPIs reduced confirmed COVID-19 deaths by more than 500 per day and reduced employment by almost 3 million.
Impact of NPIs – Contact rate

Total effect of NPIs

Decomposition by NPI

- Actual
- With no NPIs

- School closure
- Stay-at-home order
- Non-essential business closure
Impact of NPIs – Daily COVID-19 deaths

**Total effect of NPIs**
- Actual
- With no NPIs

**Decomposition by NPI**
- School closure
- Stay-at-home order
- Non-essential business closure
Impact of NPIs – Employment

Total effect of NPIs

- Actual
- With no NPIs

Decomposition by NPI

- School closure
- Stay-at-home order
- Non-essential business closure
Issuing stay-at-home orders and closing schools earlier – without ordering businesses to close – could have saved more lives and a million jobs or more.
Relative NPI efficiency

Average 30-day effect by NPI

Contact rate

- Stay-at-home order
- School closure
- Non-essential business closure

Employment

- Percent change (inverted scale)
## Policy counterfactuals

<table>
<thead>
<tr>
<th></th>
<th>Cumulative COVID-19 deaths through May 31st</th>
<th>Average difference in employment from March 1st</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Deaths</td>
<td>Difference from actual</td>
</tr>
<tr>
<td>Actual</td>
<td>114,423</td>
<td>-20.5</td>
</tr>
<tr>
<td>No NPIs</td>
<td>147,661</td>
<td>33,238</td>
</tr>
<tr>
<td>National response on March 13th</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stay-at-home order</td>
<td>120,314</td>
<td>5,891</td>
</tr>
<tr>
<td>Stay-at-home order and school closure</td>
<td>110,037</td>
<td>-4,386</td>
</tr>
<tr>
<td>Stay-at-home order, school closure, and non-essential business closure</td>
<td>102,293</td>
<td>-12,130</td>
</tr>
<tr>
<td>Local response to confirmed cases</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stay-at-home order</td>
<td>120,385</td>
<td>5,962</td>
</tr>
<tr>
<td>Stay-at-home order and school closure</td>
<td>112,798</td>
<td>-1,625</td>
</tr>
<tr>
<td>Stay-at-home order, school closure, and non-essential business closure</td>
<td>107,102</td>
<td>-7,321</td>
</tr>
</tbody>
</table>
Appendix
SEIR model

\[
\begin{align*}
\frac{dS_{it}}{dt} &= -\beta_{it}(\alpha A_{it} + I_{it}) \frac{S_{it}}{N_i} \\
\frac{dE_{it}}{dt} &= \beta_{it}(\alpha A_{it} + I_{it}) \frac{S_{it}}{N_{it}} - \sigma E_{it} \\
\frac{dA_{it}}{dt} &= (1 - \psi)\sigma E_{it} - \gamma^A A_{it} \\
\frac{dI_{it}}{dt} &= \psi\sigma E_{it} - \gamma^I I_{it} \\
\frac{dR_{it}}{dt} &= \gamma^I I_{it} \left(1 - \frac{\mu_i(t-1/\gamma^I)}{\psi}\right) + \gamma^A A_{it} \\
\frac{dT_{it}}{dt} &= \gamma^I I_{it} \left(\frac{\mu_i(t-1/\gamma^I)}{\psi}\right) \\
\frac{dD_{it}}{dt} &= \frac{\mu_i(t+\tau_F+1/\gamma^I)}{\psi} \left(\frac{I_{it}}{\tau_F - (\gamma^I)^{-1}}\right)
\end{align*}
\]

\(i = \) state (simulations) or county (estimation)
\(t = \) date
\(N_i = \) total population
\(S_{it} = \) susceptible
\(I_{it} = \) infected, symptomatic
\(A_{it} = \) infected, asymptomatic
\(E_{it} = \) exposed
\(R_{it} = \) recovered
\(T_{it} = \) terminal
\(D_{it} = \) deceased
### SEIR model – exogenous parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>ratio of asymptomatic to symptomatic transmission rates</td>
<td>1</td>
<td>Lee and others (2020), Tan and others (2020)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>$1/\tau_E$, where $\tau_E$ is the noninfectious latent period in days</td>
<td>$1/2$</td>
<td>Peng and others (2020)</td>
</tr>
<tr>
<td>$\psi$</td>
<td>symptomatic share of new infections</td>
<td>0.84</td>
<td>He and others (2020)</td>
</tr>
<tr>
<td>$\gamma^A$</td>
<td>$1/\tau_A$, where $\tau_A$ is the infectious period for asymptomatic cases in days</td>
<td>$1/7$</td>
<td>Peng and others (2020)</td>
</tr>
<tr>
<td>$\gamma^I$</td>
<td>$1/\tau_I$, where $\tau_I$ is the infectious period for symptomatic cases in days</td>
<td>$1/7$</td>
<td>Peng and others (2020)</td>
</tr>
<tr>
<td>$\tau_S$</td>
<td>duration from infectiousness onset to symptom onset</td>
<td>3</td>
<td>Lauer and others (2020), Peng and others (2020)</td>
</tr>
<tr>
<td>$\tau_F$</td>
<td>duration from symptom onset to death for severe cases in days</td>
<td>19</td>
<td>Zhou and others (2020)</td>
</tr>
<tr>
<td>$\tau_P$</td>
<td>duration from symptom onset to positive test result for confirmed cases</td>
<td>7</td>
<td>Assumed</td>
</tr>
<tr>
<td>$\mu_t$</td>
<td>infection fatality ratio</td>
<td>0.008-0.0025</td>
<td>Gu (2020)</td>
</tr>
</tbody>
</table>
Canonical SEIR model – exogenous $\mathcal{R}_{it}$

$$\mathcal{R}_{it} = \frac{\beta_{it}}{\gamma_i}$$

$$\beta_{it} = \kappa_{it} \zeta_{it}$$

$\kappa_{it}$ and $\zeta_{it}$ are exogenous

$\mathcal{R}_{it}$ = reproduction number
$\beta_{it}$ = transmission rate
$\gamma_i$ = duration of infectiousness
$\kappa_{it}$ = contact rate
$\zeta_{it}$ = infection rate
Augmented SEIR model – endogenous \( R_{it} \), NPIs, employment

\[
R_{it} = \frac{\beta_{it}}{\gamma_i}
\]

\[
\beta_{it} = \kappa_{it} \zeta_{it}
\]

\[
\kappa_{it} = \exp(\Omega_{it}^\kappa \cdot \Phi_{it}^\kappa \cdot (C_{it})^{\rho_{\kappa}})
\]

\[
\zeta_{it} \text{ is exogenous}
\]

\[
W_{it} = \exp\left(\Omega_{it}^W \cdot \Phi_{it}^W \cdot (C_{it})^{\rho_W}\right)
\]

\( R_{it} \) = reproduction number
\( \beta_{it} \) = transmission rate
\( \gamma_i \) = duration of infectiousness
\( \kappa_{it} \) = contact rate
\( \zeta_{it} \) = infection rate
\( \Omega_{it} \) = precautionary behavior
\( \Phi_{it} \) = behavioral response to NPIs
\( C_{it} \) = confirmed COVID-19 cases
\( \rho \) = infection risk response elasticity
\( W_{it} \) = employment (number of workers)
Behavioral parameter estimation

Ideally, we would estimate behavioral parameters from historical $R_{it}$:

$$\ln R_{it} = \omega_t X_i + \phi P_{it} + \rho c_{it} + \ln \zeta_{it} - \ln \gamma_i$$

$X_i = \text{county demographics, labor force characteristics, 2016 Republican vote share}$

$\omega_t = \text{precautionary response parameters}$

$P_{it} = \text{state and local NPI event study indicators}$

$\phi = \text{NPI response parameters}$

Not feasible to estimate directly because $R_{it}$ is only measurable once the epidemic is already underway → lose sample coverage of initial response in many counties.
Parameter estimation

We estimate parameters using the contact rate $\kappa_{it}$ instead of $R_{it}$:

$$\ln \kappa_{it} = \omega_t^\kappa X_i + \phi_t^\kappa P_{it} + \rho_t^\kappa c_{it}$$

Same specification for employment:

$$\ln W_{it} = \omega_t^W X_i + \phi_t^W P_{it} + \rho_t^W c_{it}$$
NPI event study treatment effects – Contact rate

\[ \ln \kappa_{it} = \omega_t^\kappa X_i + \phi^\kappa P_{it} + \rho^\kappa c_{it} \]
NPI event study treatment effects – Employment

\[ \ln W_{it} = \omega^W_t X_i + \phi^W P_{it} + \rho^W c_{it} \]
Decomposition of response to COVID-19 by state
Decomposition of response to COVID-19 by state