

### **Budget Model**

# Epidemiological and Economic Effects of Lockdown

Alexander Arnon, John Ricco, and Kent Smetters

September 2020

#### Background – Shutting down



#### 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 31<sup>st</sup> 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:

*transmission rate* = *contact rate* × *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  $\rightarrow$  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

**Wharton** 



**Budget Model** 

## Declines in contacts and employment were mostly voluntary action, not government mandates.





#### Decomposition of response to COVID-19





#### Precautionary contact rate response and political preference





#### Precautionary employment response and industry



Quartile of leisure and food services share - 1 - 2 - 3 - 4



## NPIs reduced confirmed COVID-19 deaths by more than 500 per day and reduced employment by almost 3 million.



#### Impact of NPIs – Contact rate



PENN WHARTON Budget Model

Wharton

#### Impact of NPIs – Daily COVID-19 deaths



#### Impact of NPIs – Employment



- 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

#### Policy counterfactuals

	Cumulative COVID-19 deaths through May 31st		Average difference in employment from March 1st	
	Deaths	Difference from actual	Millions	Difference from actual
Actual	114,423		-20.5	
No NPIs	147,661	33,238	-17.8	2.67
National response on March 13th				
Stay-at-home order	120,314	5,891	-18.9	1.62
Stay-at-home order and school closure	110,037	-4,386	-19.5	1.01
Stay-at-home order, school closure, and non-essential business closure	102,293	-12,130	-21.6	-1.08
Local response to confirmed cases				
Stay-at-home order	120,385	5,962	-18.8	1.76
Stay-at-home order and school closure	112,798	-1,625	-19.3	1.21
Stay-at-home order, school closure, and non-essential business closure	107,102	-7,321	-21.1	-0.62

## Appendix





#### SEIR model

 $\frac{dS_{it}}{dt} = -\beta_{it}(\alpha A_{it} + I_{it})\frac{S_{it}}{N_i}$  $\frac{dE_{it}}{dt} = \beta_{it}(\alpha A_{it} + I_{it})\frac{S_{it}}{N_{it}} - \sigma E_{it}$  $\frac{dA_{it}}{dt} = (1 - \psi)\sigma E_{it} - \gamma^A A_{it}$  $\frac{dI_{it}}{dt} = \psi \sigma E_{it} - \gamma^I I_{it}$  $\frac{dR_{it}}{dt} = \gamma^{I} I_{it} \left( 1 - \frac{\mu_{i(t-1/\gamma^{I})}}{\psi} \right) + \gamma^{A} A_{it}$  $\frac{dT_{it}}{dt} = \gamma^{I} I_{it} \left( \frac{\mu_{i(t-1/\gamma^{I})}}{\eta b} \right)$  $\frac{dD_{it}}{dt} = \frac{\mu_{i(t+\tau_F+1/\gamma^I)}}{\psi} \left(\frac{I_{it}}{\tau_F - (\gamma^I)^{-1}}\right)$ 

- *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

Parameter	Definition	Value	Source
α	ratio of asymptomatic to symptomatic transmission rates	1	Lee and others (2020), Tan and others (2020)
σ	$1/ au_{E}$ , where $ au_{E}$ is the noninfectious latent period in days	1/2	Peng and others (2020)
$oldsymbol{\psi}$	symptomatic share of new infections	0.84	He and others (2020)
$\gamma^A$	$1/\tau_A$ , where $\tau_A$ is the infectious period for asymptomatic cases in days	1/7	Peng and others (2020)
$\gamma^{I}$	$1/\tau$ , where $\tau_{I}$ is the infectious period for symptomatic cases in days	1/7	Peng and others (2020)
$ au_S$	duration from infectiousness onset to symptom onset	3	Lauer and others (2020), Peng and others (2020)
$ au_F$	duration from symptom onset to death for severe cases in days	19	Zhou and others (2020)
$ au_P$	duration from symptom onset to positive test result for confirmed cases	7	Assumed
$\mu_t$	infection fatality ratio	0.008-0.0025	Gu (2020)

#### 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

 $\mathcal{R}_{it} = \text{reproduction number}$  $\beta_{it} = \text{transmission rate}$  $\gamma_i = \text{duration of infectiousness}$  $\kappa_{it} = \text{contact rate}$  $\zeta_{it} = \text{infection rate}$ 



#### Augmented SEIR model – endogenous $\mathcal{R}_{it}$ , NPIs, employment

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

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

$$\kappa_{it} = \exp\left(\Omega_{it}^{\kappa} \cdot \Phi_{it}^{\kappa} \cdot (C_{it})^{\rho^{\kappa}}\right)$$

 $\zeta_{it}$  is exogenous

$$W_{it} = \exp\left(\Omega_{it}^W \cdot \Phi_{it}^W \cdot (C_{it})^{\rho^W}\right)$$

- $\mathcal{R}_{it}$  = 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  $\mathcal{R}_{it}$ :

$$\ln \mathcal{R}_{it} = \underbrace{\boldsymbol{\omega}_{t} X_{i}}_{\Omega_{it}} + \underbrace{\boldsymbol{\phi}_{it}}_{\Phi_{it}} + \rho c_{it} + \ln \zeta_{it} - \ln \gamma_{i}$$
$$\Omega_{it} \quad \Phi_{it}$$

 $X_i$  = county demographics, labor force characteristics, 2016 Republican vote share

- $\boldsymbol{\omega}_t$  = precautionary response parameters
- $P_{it}$  = state and local NPI event study indicators
- $\phi$  = NPI response parameters

Not feasible to estimate directly because  $\mathcal{R}_{it}$  is only measurable once the epidemic is already underway  $\rightarrow$  lose sample coverage of initial response in many counties.

#### Parameter estimation

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

$$\ln \kappa_{it} = \underbrace{\boldsymbol{\omega}_{t}^{\kappa} X_{i}}_{\Omega_{it}^{\kappa}} + \underbrace{\boldsymbol{\phi}^{\kappa} P_{it}}_{\Phi_{it}^{\kappa}} + \rho^{\kappa} c_{it}$$

Same specification for employment:

$$\ln W_{it} = \underbrace{\boldsymbol{\omega}_{t}^{W} X_{i}}_{\Omega_{it}^{W}} + \underbrace{\boldsymbol{\phi}^{W} P_{it}}_{\Phi_{it}^{W}} + \rho^{W} c_{it}$$



#### NPI event study treatment effects – Contact rate



 $\ln \kappa_{it} = \boldsymbol{\omega}_t^{\kappa} X_i + \boldsymbol{\phi}^{\kappa} P_{it} + \rho^{\kappa} c_{it}$ 



#### NPI event study treatment effects – Employment



 $\ln W_{it} = \boldsymbol{\omega}_t^W X_i + \boldsymbol{\phi}^W P_{it} + \rho^W c_{it}$ 



#### Decomposition of response to COVID-19 by state

Contact rate



#### Decomposition of response to COVID-19 by state

Employment





**Budget Model**