How Should Policy Responses to the COVID-19 Pandemic Differ in the Developing World?

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Policy Responses to COVID-19 So Far

The West (US and Europe)

- Blanket lockdowns
- Substantial unemployment insurance + direct cash transfers

Developing countries

- Blanket lockdowns
- Not so extensive transfers
- Infections rising rapidly now – policymakers unclear how to respond

This Paper: How Policy Should Differ in Developing Countries

Preliminary analysis using incomplete-markets macro model with disease spread

Key reasons for different policy responses

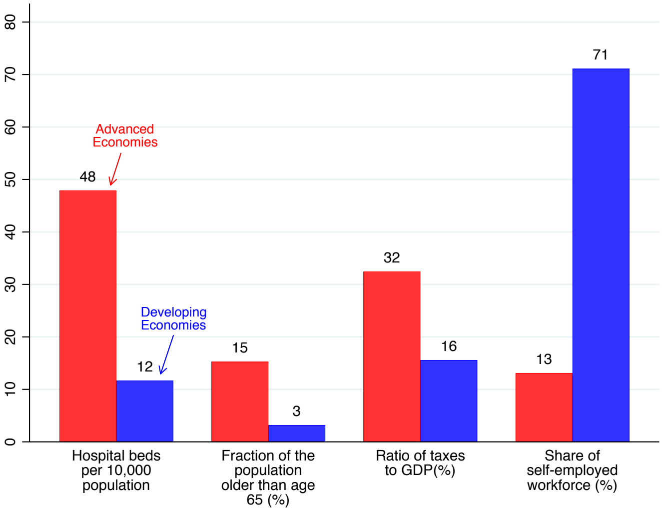
1. Younger populations
2. Less fiscal capacity
3. Large informal sector
4. Less healthcare capacity
5. More hand-to-mouth households

Quantitative Results from Our Model (So Far)

- Blanket lockdowns much less effective in developing countries
  - Save around half as many lives per GDP lost
- Yet blanket lockdowns still better than no lockdowns
- Age-dependent policy even more effective in developing countries
  - Save more lives per unit of GDP lost
  - Lower fiscal & economic cost of shielding old, since so few of them

Developed vs Developing Countries: Key Differences Relevant for the Pandemic

Developed vs Developing Countries: Key Differences



Model

Outline of the Model

Epidemiology

- SICR with age heterogeneity as in Glover et al. (2020)

Households

- Face uninsured idiosyncratic labor income risk and health risk
- Accumulate assets endogenously, face credit constraint

Sectors

- Formal: "skilled production"
- Informal: "unskilled production," cannot enforce lockdowns or collect taxes

Government

- Collects taxes and makes transfers but with limited fiscal capacity

Households and Preferences

- Two "age groups": young (ω) and old ($1 - \omega$)
- Preferences (of the living):

$$\mathbb{E}\left[\sum_{t=0}^{\infty} \beta_j^t \left\{\log(c_t) + \bar{u}\right\}\right]$$

- β_j is discount factor of age group j, where $j \in \{y, o\}$
- $\bar{u}$: flow utility of being alive

Permanent Productivities and Idiosyncratic Shocks: Roy Meets Aiyagari

- Individuals endowed with vector of permanent productivities $\{z, 1\}$ in formal and informal sectors, as in Roy (1951)
- Formal sector productivity $z \sim G$
- Individuals face idiosyncratic productivity shock as in Aiyagari (1994)

$$\log v_{t+1} = \rho_v \log v_t + \varepsilon_{t+1} \quad \text{with} \quad \varepsilon_{t+1} \overset{iid}{\sim} F(0, \sigma_v)$$

- Individuals choose sector each period

Health Shocks

- Being infected drops all productivities by fraction $0 < \eta \leq 1$ until recovery
- Being critical drops all productivities to 0 until recovery
- Death means $\bar{u}$ is lost permanently

Lockdown Technology

Lockdown lowers productivity and infection rate for everyone in the formal sector

- Productivity z goes down to $\lambda_w z$, $0 < \lambda_w \leq 1$
- Probability of becoming infected goes down by fraction $1 - \lambda_h$ $(0 < \lambda_h \leq 1)$
- Lower λ_w and λ_h means stricter lockdown

Production and Firm Profit Maximization

- Final good technology (Ulyssea 2018):

$$
\begin{aligned}
Y &= L^{\alpha} K^{1-\alpha}, \quad 0 < \alpha \leq 1 \\
K &= K^D + K^F \\
L &= \left[A L_f^{\frac{\sigma-1}{\sigma}} + L_i^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}
\end{aligned}
$$

- A is the exogenous productivity of formal sector (Caselli-Coleman, 2006)
- K^D and K^F are domestic and foreign capital, respectively.
- Capital rented at r^F, an exogenously given international rental rate

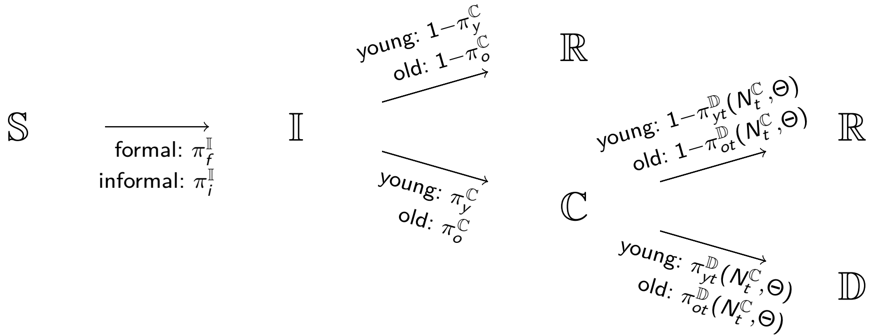
Assets and Individual's Budget Constraint

Precautionary savings generate endogenous asset distribution

- Individuals can save at gross interest rate $R = 1 + r^F - \chi$
- χ is the "financial wedge" between return on saving and world market
- Borrowing not allowed
- Individual's budget constraint (assuming no lockdown):

$$c + a' \leq \mathbb{1}_{\{s=i\}} w_i v + (1-\tau)\mathbb{1}_{\{s=f\}} w_f z v + (1+r)a + T$$

Health States and Transitions



Hospital Capacity

- Θ is maximum ICU capacity per capita $(0 < \Theta < 1)$
- Probability of receiving an ICU bed is $\min\{\frac{\Theta}{N_t^{\mathbb{C}}}, 1\}$
- Fatality rate $\pi_{jt}^{\mathbb{D}}$:

$$\pi_{jt}^{\mathbb{D}}(N_t^{\mathbb{C}}, \Theta) = \begin{cases} \pi_j^{\mathbb{D}} & \text{if assigned ICU bed} \\ \kappa \times \pi_j^{\mathbb{D}} & \text{if not assigned} \end{cases}$$

- $\pi_j^{\mathbb{D}}$: baseline fatality rate of an age group j patient
- κ governs the impact of hospital overuse on fatality rate

Quantitative Analysis

Quantitative Analysis

- Solve for stationary distribution of model and calibrate two versions: "advanced economy" and "developing economy"
- Pandemic introduced as "MIT shock" – no one saw it coming (actually realistic!) but perfect information since (still crazy)
- Solve full transition path in both economies under various lockdown policies

Calibration of Economic Parameters

Var	Description	Value	Source / Target
r^F	Exogenous interest rate	0.0006	Pre-COVID T-Bills rate 1.5%
ϕ	Shape-parameter of Frechet distribution G	2.7	Lagakos and Waugh (2013)
ρ_v	Persistence of idiosyncratic income shock	0.91	Floden and Linde (2001)
σ_v	St.Dev of idiosyncratic income shock	0.04	Floden and Linde (2001)
α	Labor share	0.6	Gollin (2002)
β_y	Discount factor for the young	0.9984	Glover et al. (2020)
β_o	Discount factor for the old	0.9960	Glover et al. (2020)

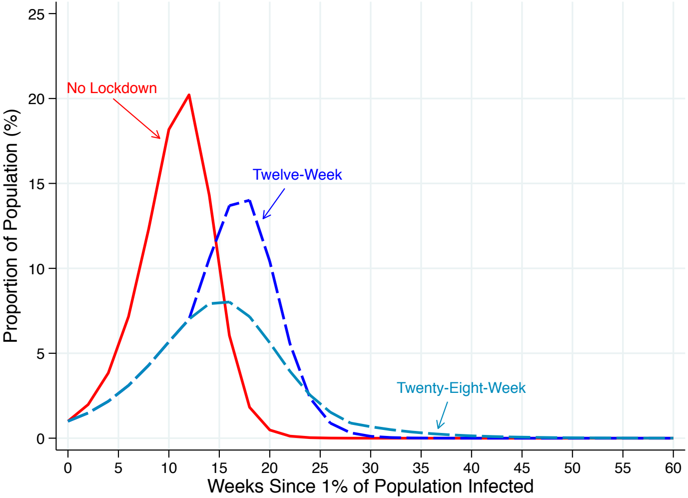
Calibration of Epidemiological Parameters

Var	Description	Value	Source or Target
η	Effect of infection on productivity	0.8	Asymptomatic cases
κ	Impact of hospital overuse on fatality	2	Glover et al. (2020)
λ_w	Effect of lockdown on productivity	0.68	Blandin and Bick (2020)
λ_h	Effect of lockdown on infection rate	0.75	U.S. cumulative infections
$\pi_y^{\mathbb{C}}$	Rate of young entering $\mathbb{C}$ from $\mathbb{I}$	3.4%	Ferguson et al. (2020)
$\pi_o^{\mathbb{C}}$	Rate of old entering $\mathbb{C}$ from $\mathbb{I}$	19.9%	Ferguson et al. (2020)
$\pi_y^{\mathbb{D}}$	Rate of young entering $\mathbb{D}$ from $\mathbb{C}$	2.8%	Ferguson et al. (2020)
$\pi_o^{\mathbb{D}}$	Rate of old entering $\mathbb{D}$ from $\mathbb{C}$	10.9%	Ferguson et al. (2020)
$\beta^{\mathbb{I}}$	Behavior-adjusted infection generating rate	2.0	Peak Infection Rates

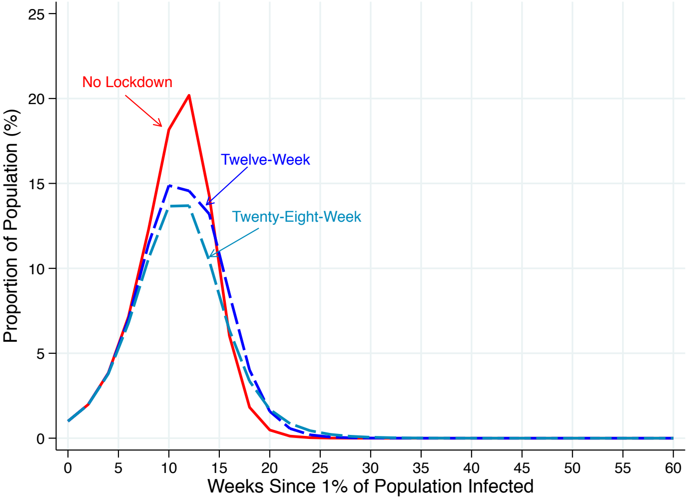
Parameters Varying between Advanced and Developing Economies

Var	Description	Advanced Economies	Developing Economies	Source or Target
A	Formal sectors TFP	3.0	0.15	1% labor informality in US
$\bar{u}$	Flow value of being alive	$11.4\bar{c}^{US}$	$11.4\bar{c}^{DEV}$	Glover et al. (2020)
χ	Spread b/w borrowing and lending	0	0.66%	Donovan (2019)
τ	Marginal tax rate	0.25	0.15	Besley and Persson (2013)
Δ	Iceberg cost in tax collection	1	2.22	Dzansi et al. (2013)
$\bar{B}$	Lockdown emergency transfers	1%	0.1%	Lockdown transfer programs
ω	Share of young in population	73%	92%	2018 ACS / World Bank
Π	Int' aid / natural resources revenue	0	10% of GDP	World Bank
Θ	Hospital capacity per capita	0.00042	0.00011	Glover et al. (2020) / WHO

Simulated COVID-19 Infection Rates, Advanced Economy



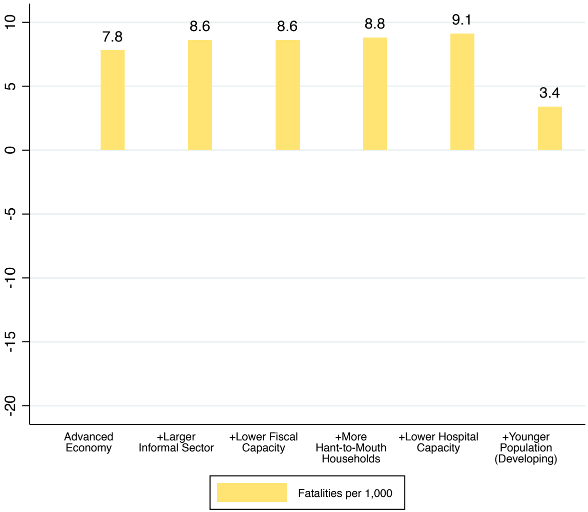
Simulated COVID-19 Infection Rates, Developing Economy



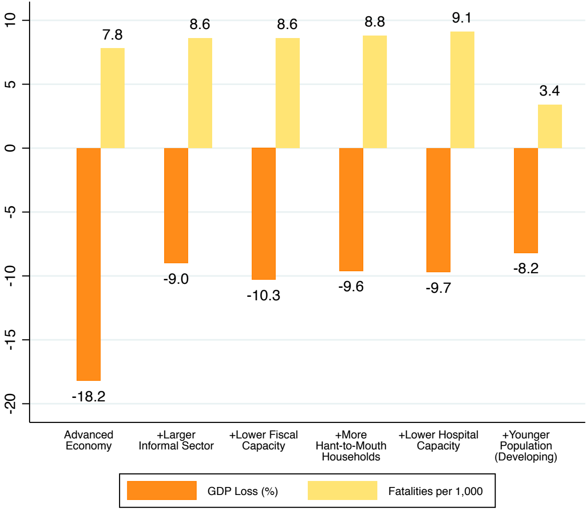
Model Predictions: Effects of the COVID-19 Pandemic

	Lifetime Welfare (%)	GDP (%)	Fatalities per 100,000 People
Advanced Economies			
No Lockdown	-8.3	-1.8	$1,102$
Twenty-Eight-Week Lockdown	-5.5	-18.2	778
Panel B: Developing Economies			
No Lockdown	-4.1	-1.1	412
Twenty-Eight-Week Lockdown	-3.6	-8.2	340

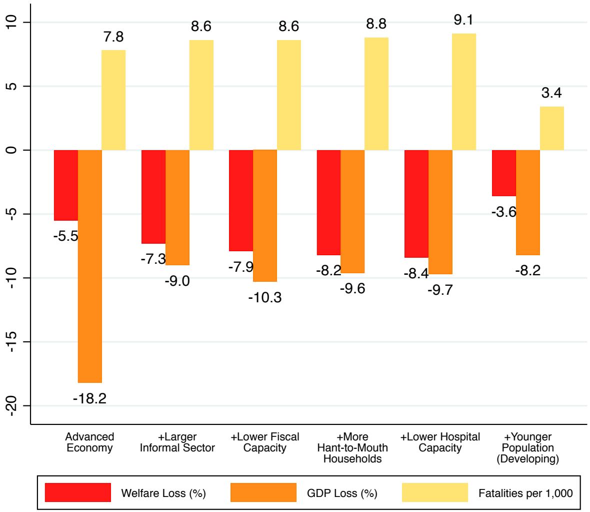
Counterfactuals: Cumulative Contributions (28-Week Lockdown)



Counterfactual: Cumulative Contributions (28-Week Lockdown)



Counterfactual: Cumulative Contributions (28-Week Lockdown)



Age-Dependent Lockdowns a.k.a. "Shielding the Elderly"

- Highly heterogeneous effects by age suggest role for age-dependent policies
- Studied in U.S. by Acemoglu, Chernozhukov, Werning and Whinston (2020), Bairolyia & Imrohoroglu (2020) and others
- Model as lockdown only of old, with transfers only to old

Lives Saved per 100,000 People for every Point of GDP Lost

	Advanced Economy		Developing Economy	
	Blanket Lockdown	Age-dependent Lockdown	Blanket Lockdown	Age-dependent Lockdown
Twenty-Eight-Week	19.8	54.0	10.2	95.2

Lives Saved per 100,000 People for every Point of GDP Lost

	Advanced Economy		Developing Economy	
	Blanket Lockdown	Age-dependent Lockdown	Blanket Lockdown	Age-dependent Lockdown
Twenty-Eight-Week	19.8	54.0	10.2	95.2

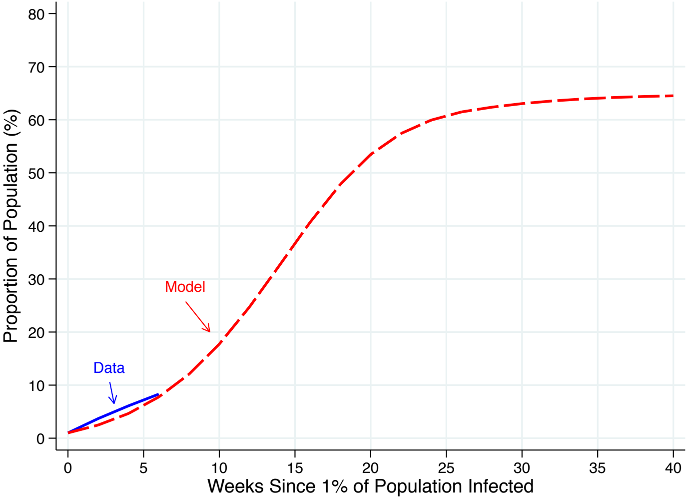
$\rightarrow$ More potent in developing economy since only 8% old, compared to 27% in advanced economy, and enough fiscal capacity for transfers to old

Conclusions and Future Work

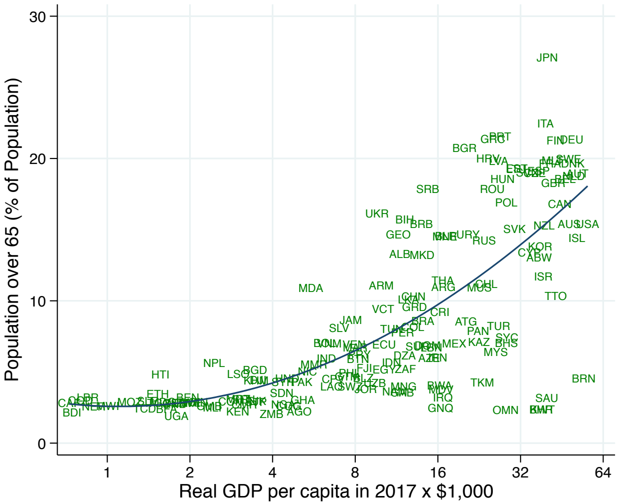
- Blanket lockdowns better than nothing in developing economies, but not real effective
- Case for "shielding the old" rather than blanket lockdowns even stronger in developing countries
- Lots of caveats and better data needed to draw firmer conclusions
- Future work: adding back children, intergenerational household structure, policy analysis of school openings

Extra Slides

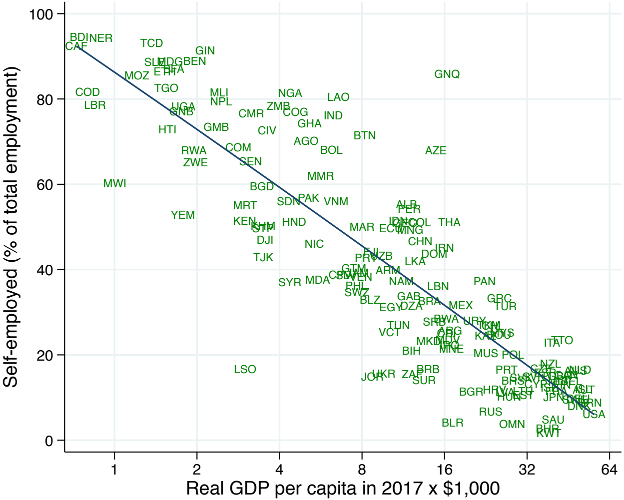
Model Fit of Cumulative Infection Cases in the United States



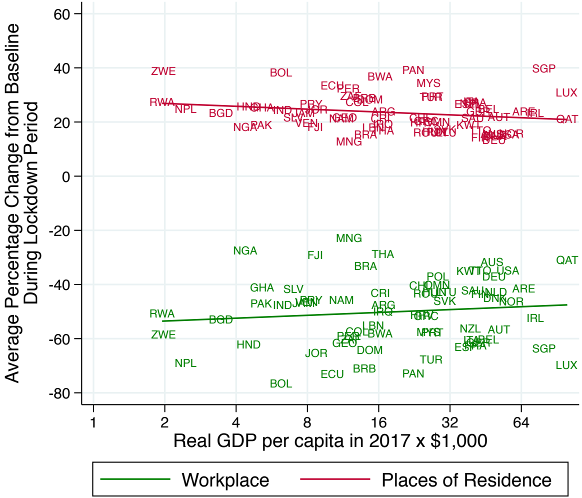
Share of Population Above Age 65



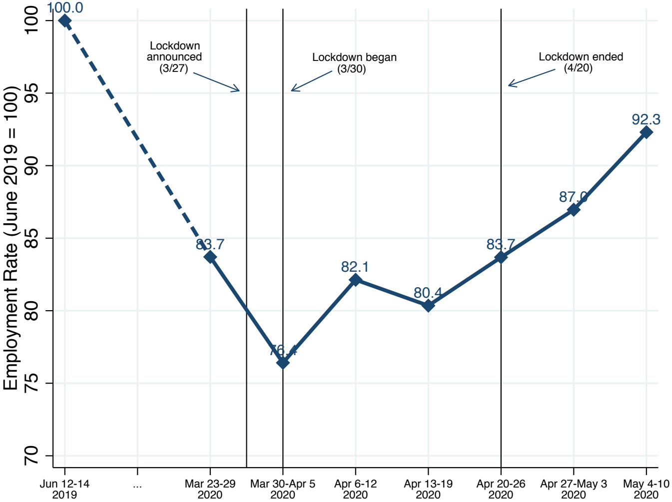
Share fo Self-Employed Workforce



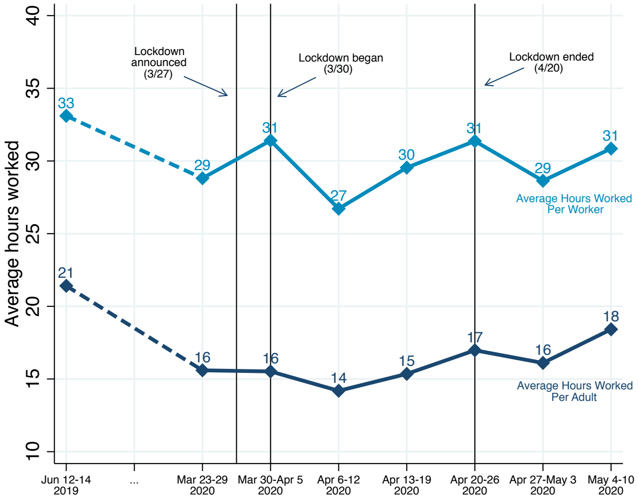
Changes in Mobility Across Countries During Lockdown Periods



Employment Rate in Ghana Around the Lockdown Period



Hours Worked in Ghana Around the Lockdown Period



Mobility in Ghana Around the Lockdown Period

Borrowing During Pandemic

- Countries can access to emergency bonds B_t
- Used to finance additional welfare transfers during government imposed lockdowns
- Funds borrowed accrue interest at rate $1 + r^F$ until the pandemic ends
- They are repaid through annual annuities after the pandemic ends

$$B_t = \begin{cases} \bar{B} & \text{during the lockdown} \\ -\frac{r^F}{1+r^F} \times \sum_{t_l - t_s}^{t_l - t_e} \left(1 + r^F\right)^t \ \bar{B} & \text{after pandemic ends} \\ 0 & \text{otherwise} \end{cases}$$

Calibrating Epidemiology Parameters: Entering Critical Stage

- Ferguson et al. (2020) report the average duration of time individuals spend in infectious stage is 13 days (5 days in asymptomatic + 8 days in symptomatic)
- We assume the duration is 14 days
- We assume 50% of infectious people are asymptomatic (there's no good estimate)
- Define old as > 60 yrs old, exclude < 15 yrs old
- Compute the weighted average of the percentage of hospitalized cases requiring critical care, using weights equal to the percentage of the US population for different age groups (from 2018 ACS)
- This gives us

$$\pi_y^{\mathbb{C}} = 6.85\% \times \frac{1}{2} = 3.43\%$$
$$\pi_o^{\mathbb{C}} = 39.75\% \times \frac{1}{2} = 19.88\%$$

Calibrating Epidemiology Parameters: Fatality Rates

- Ferguson et al. (2020) report the average duration of time individuals spend in the critical condition stage is 10 days. We assume the duration is 14 days
- Using Table 1 in Ferguson et al. (2020), infection fatality ratio adjusted to the US population distribution is 0.18% for young and 4.32% for old.
- Back out $\pi_j^{\mathbb{D}}$ using the formula

$$\pi_y^{\mathbb{C}} \times \pi_y^{\mathbb{D}} = 0.18\%$$
$$\pi_o^{\mathbb{C}} \times \pi_o^{\mathbb{D}} = 4.32\%$$

- This gives us

$$\pi_y^{\mathbb{D}} = 2.76\%$$
$$\pi_o^{\mathbb{D}} = 10.86\%$$

Contact Patterns at Workplace Similar Across Countries

Working place contacts are least assortative

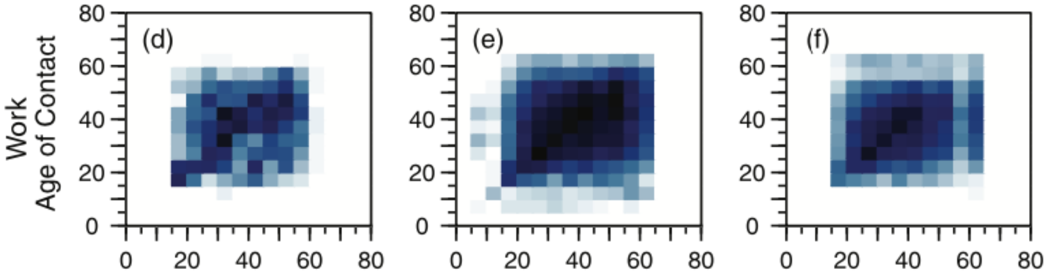


Figure: Age-specific contact patterns at workplace, Germany, Bolivia, and South Africa. x-axis is the age of individual. *Source*: Prem, Cook, and Jit (2017) PLOS Computational Biology

Contact Patterns at Home Vary Across Countries

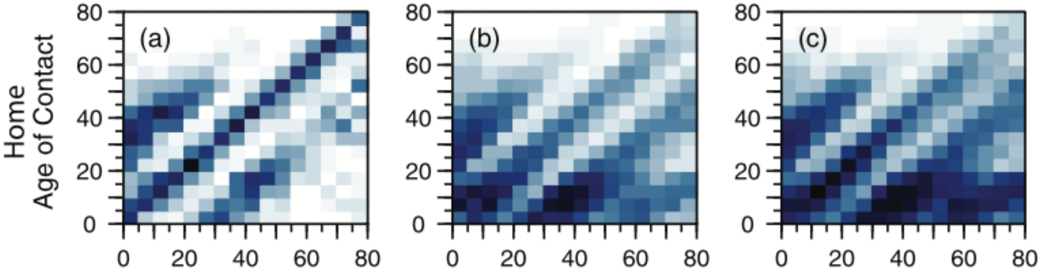


Figure: Age-specific contact patterns at home, Germany, Bolivia, and South Africa. *x*-axis is the age of individual. *Source*: Prem, Cook, and Jit (2017) PLOS Computational Biology

Contact Patterns at School

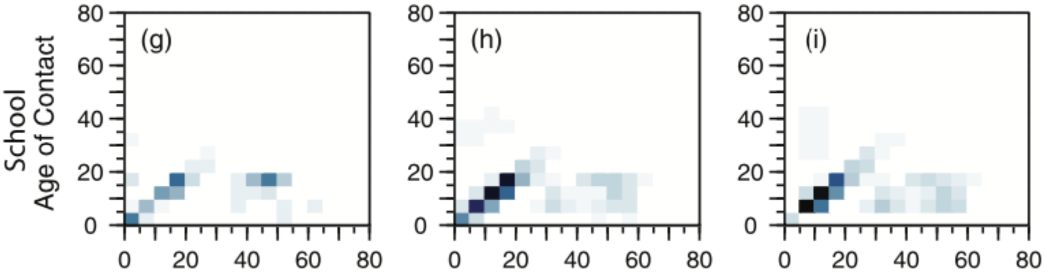


Figure: Age-specific contact patterns at school, Germany, Bolivia, and South Africa. *x*-axis is the age of individual. *Source*: Prem, Cook, and Jit (2017) PLOS Computational Biology

Cohabitation and Contact Patterns

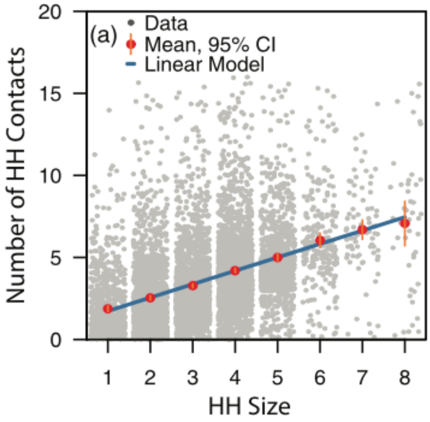


Figure: Number of contacts at home made by individuals in the POLYMOD study stratified by household sizes. *Source*: Prem, Cook, and Jit (2017) PLOS Computational Biology