Optimal Age-based Policies for Pandemics: An Economic Analysis of Covid-19 and Beyond

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Introduction

- Many infectious diseases are more deadly for the elderly
- Covid-19 in particular
- Should policy confine the old and allow the young to work?
- Would the old already confine themselves?
- Economic-epidemiological model
    - Individual choice
    - Age heterogeneity
    - Incomplete information (role for testing)

Literature: Economics and infectious diseases

Pre-Covid:

- Kremer (QJE 1996): seminal theory paper (HIV).
- Greenwood, Kircher, Santos and Tertilt (Ecma 2019): first quantitative economic model of infectious diseases (HIV).

Covid:

- Eichenbaum, Rebelo and Trabandt (RFS 2021): individual behavior, but no age. (See also: Farboodi et al 2020, Garibaldi et al 2020, Assenza et al 2020, McAdams 2020,...)
- Covid19 literature with young and old agents:
  - argues for a policy that focuses on confinement of the old: Acemoglu et al, Alon et al, Bairoliya and Imrohoroglu, Favero et al
- Many, many other works.

Main findings

- Model calibrated to the Covid-19 epidemic in the US
- Older individuals shield themselves substantially in laissez-faire, the young less so
- Self-protecting behavior decreases deaths by 2/3
- Optimal lockdown: no-Covid strategy, deaths $\downarrow$ 96%
  - Planner confines the young more, the old less than in laissez-faire
  - Contrary to the literature: Acemoglu et al. (2021), Alon et al. (2020), Bairoliya and Imrohoroglu (2020), Favero et al. (2020), Gollier (2020)
  - Why different results? Other papers can't know laissez-faire: no endogenous behavior
- Other exercises: Spanish flu, synthetic diseases, testing

Outline

Outline

Model

- Discrete time
- Two ages (a): young (y) and old (o)
- Agents can get Covid when meeting other infected.
- Seasonality in transmission.
- Cannot tell Covid from common cold.
- Testing probability: ξ_t
- All of the above depend on age a
- Unexpected Covid arrival, stochastic vaccine arrival

Model: Health States

- Susceptible (s)
- Fever (f): unsure whether Covid (f_i) or common cold (f_s)
- Infected (i): recovery ($\phi(0)$) or serious symptoms (α)
- Hospitalized (h): recovery ($\phi(1)$) or death (δ)
- Recovered (r): immune forever

Model: choices

- Time: work outside n, telework v, leisure outside ℓ, domestic leisure d
- Time constraint: $n + \ell + d + v = 1$
- Leisure good outside the house g:

$$g(x, \ell) = [\theta x^{\rho} + (1 - \theta)\ell^{\rho}]^{1/\rho} \tag{1}$$

- Utility function:

$$u(c, g, d) = b + \ln(c) + \gamma \ln(g) + \lambda \ln(d) \tag{2}$$

- Income of young agent: $w[n + (\iota_0 - \iota_1 v)v]$
- Income of old agent: $\bar{w}$
- Budget constraint: $c + x = \text{income}$

Model: government lockdowns

- Lockdowns: tax τ on time spent outside the house (both work n and leisure ℓ).
- Interpretation: additional time preparing trips, filling out forms, constraints on meeting friends etc.
- Taxes can condition on time period and age, but not on health state: $\tau(t, a)$
- Implies that an individual who aims to spend $\tilde{n}$ units of time at work gets paid only for $n = \tilde{n}(1 - \tau)$.
- Since a day always has 24 hours, we rebate the time tax lump-sum to households.
- Example: Covid restrictions make a commute longer but use time to listen to a podcast.

Model: infections

- Prob. of agent catching Covid: $\pi(n+\ell,\Pi_t) = (n+\ell+\underline{m})\Pi_t$
- Prob. of agent catching a common cold: $\pi^*(n+\ell,\Pi_t^*) = (n+\ell+\underline{m})\Pi_t^*$
- Assume Covid and the common cold are mutually exclusive events (good approximation if probabilities of either event is sufficiently small).
- Uncertain agent's belief of having Covid in t: $\Pi_{t-1}/(\Pi_{t-1}+\Pi_{t-1}^*)$
- Prob. of getting Covid per fraction of the period spent outside (general equilibrium):

$$\hat{\Pi}_t = \Pi_0\psi_t \sum_{a,j\in\{f_i,i,h\}} (n_t(j,a)+\ell_t(j,a)+\underline{m})\, M_t(j,a) \tag{3}$$

- Prob. of getting infected in t:

$$\Pi_t = 1 - e^{-\hat{\Pi}_t} \tag{4}$$

Model: infections

Covid:

$$\pi(n+\ell,\Pi_t(a)) = \underbrace{(n+\ell+\underline{m})}_{\text{Prob. entering common space}}\Pi_t(a)$$

Common cold:

$$\pi^*(n+\ell) = (n+\ell+\underline{m})\Pi^*$$

Covid transmission probability:

$$\hat{\Pi}_t(a) = \Pi_0\psi_t \underbrace{\sum_{a',j\in\{f_i,i,h\}} \left(n_t(j,a') + \ell_t(j,a') + \underline{m}\right) M_t(j,a')}_{\text{other infected per square meter}}$$

$$\Pi_t(a) = \underbrace{1 - e^{-\hat{\Pi}_t(a)}}_{\text{continuous time aggregation}}$$

Model: value functions

- Susceptible agent:

$$V_t(s,a) = \max_{c,x,n,v,\ell,d} u(c, g(x,\ell), d) \tag{5}$$
$$+ \beta(a)[1 - \pi_f(n+\ell, \Pi_t, \Pi_t^*) + \pi^*(n+\ell, \Pi_t^*)\xi_t(a)]W_{t+1}(s,a)$$
$$+ \beta(a)\xi_t(a)\pi(n+\ell, \Pi_t)W_{t+1}(i,a)$$
$$+ \beta(a)(1-\xi_t(a))\pi_f(n+\ell, \Pi_t, \Pi_t^*)W_{t+1}(f,a)$$

s.t. budget and time constraints, where

$$W_{t+1}(j,a) = \chi_t V^*(j,a) + (1-\chi_t)V_{t+1}(j,a) \tag{6}$$

- We'll skip the other value functions and laws of motion of aggregate distributions

▸ Other value functions

Model: testing

- Testing probability ξ_t is a general equilibrium variable:

$$\xi_t(a) = \min\left\{\frac{\text{Total test capacity in } t}{\text{Total number of testable agents in } t}, 1\right\} \tag{7}$$

- We explore counterfactuals where $\xi_t(a)$ indeed varies across ages

Equilibrium & Aggregation

- All agents solve individual optimization problem.
- Laws of motion: as you would expect
- Covid prevalence: determined by behavior (of infected and susceptible) and # infected last period.
- Output: sum of wages

Outline

Calibration

- Time period: one week
- Old: ≥ 65 years
- Set 1: parameters externally calibrated
  - Disease parameters (to fit CFR, Covid duration, ...)
  - Utility parameters (time usage before Covid)
  - Value of a statistical life: 9.3 million dollars
- Set 2: parameters calibrated to replicate Covid-19 time series

▸ Externally calibrated parameters

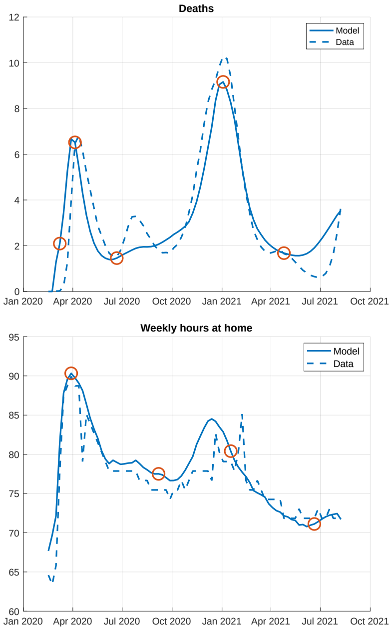
Table: Moments – Model vs. Data

Moment	Model	Data (ranges)
Common colds per year	3	2-4
% of infected in critical care, young	3.33	3.33
% of infected in critical care, old	9.10	9.10
% in critical care that dies, young	14.2	5-24
% in critical care that dies, old	65.0	40-73
Weeks in critical care, young	3.5	3-6
Weeks in critical care, old	3.5	3-6
Hours/day interacting while in ICU	3.8	7.6 (controlled)
Life expectancy (natural), young	∞	79
Life expectancy (natural), old	20	20
Value of statistical life (in million US$)	9.3	9.3
Hours of work per week	40	40
% of weekly hours in telework (normal times)	8	8
% $\downarrow$ in output w/ 36% of workers in telework	10	10
Hours of outside activities per week	17.3	17.3
% of income on goods outside	12.5	11.1-16.1
Replacement rate - social security, %	60	46-64

Table: Calibration – Internally calibrated parameters

Parameter	Value	Interpretation
Π_0	6.011	Infectiousness of Covid-19
$\bar{\psi}$	1.51	Peak of infectiousness during winter
η_0	4.33e-6	Stringency index function
η_1	2.553	Stringency index function
$\bar{\tau}_i$	0.379	Time tax rate for isolation (positive tests)
$\underline{m}$	0.143	Exogenous Covid infections
I_0	0.0011	Initial fraction of infected people

- $\tau_t = \tau_t(j, a) = \eta_0(\text{Stringency index in } t)^{\eta_1}$ for $j \in \{s, f, r\}$ and all a
- $\tau_t(i, a) = \max\{\bar{\tau}_i, \tau_t\}$
- Last data target: $R_0 = 3$ (during winter peak)

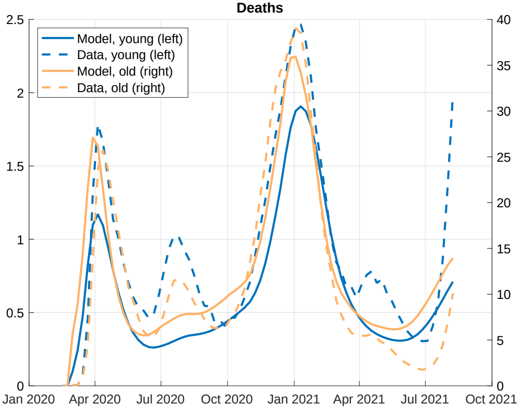


Non-targeted moments

- Deaths by age
- Time outside by age
- Employment
- Test positivity rate

Death by Age over Time

Figure: Deaths by age



Decline in Time Outside

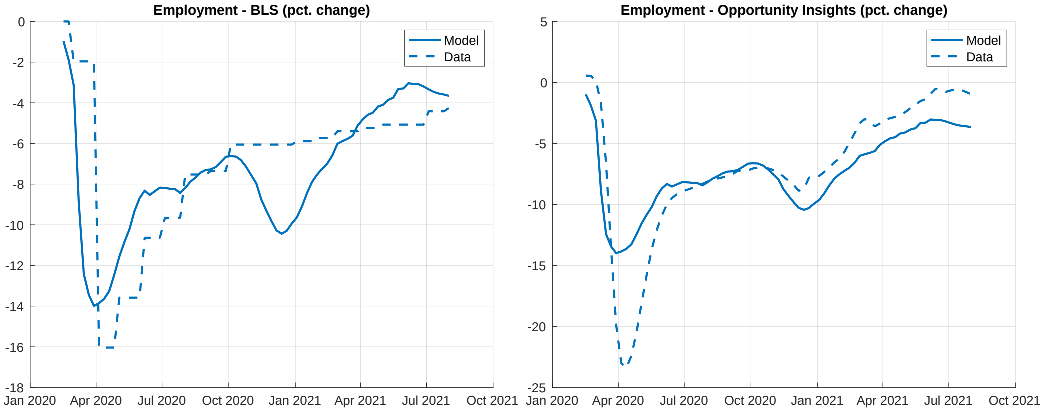
Table: Change in (non-work) time outside by age, model versus data

	May–July		May–December	
	Model	Data	Model	Data
Young	-12.0	-24.9	-11.1	-16.1
Old	-35.4	-31.4	-47.4	-28.9

Note: Data from the American Time Use Survey (ATUS). Declines relative to the same months in 2019.

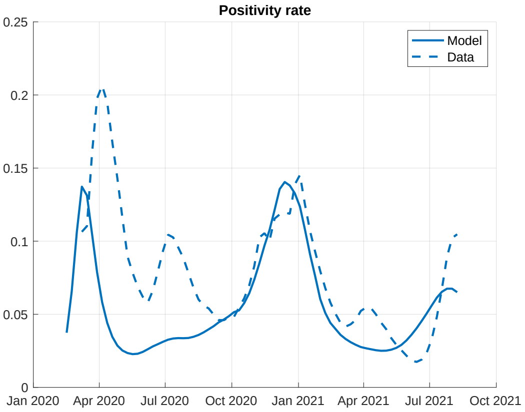
Employment over Time

Figure: Outside work choices of the young



Test Positivity Rate

Figure: Test positivity rate



Outline

Benchmark vs. Epidemiological Model

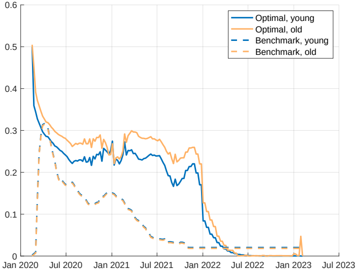
		Benchmark	Epidemiological	No lockdown
Hrs @ home - avg. first year,	Young	17.01	0	6.87
diff. w.r.t. no-disease	Old	11.55	0	14.47
Dead p/ 1,000 (by vaccine arrival)	Young	0.5	1.81	1.02
	Old	9.74	50.03	17.08
	All	2.48	12.12	4.46
Recovered, % (by vaccine arrival)	Young	23.13	78.74	44.84
	Old	10.61	51.44	17.89
	All	20.45	72.9	39.07
GDP 1 year, % change w.r.t. no-disease		-12.96	-1.44	-5.77

Voluntary cautious behavior saved many lives! Government lockdown saved additional lives but at sizeable GDP cost. Worth it?

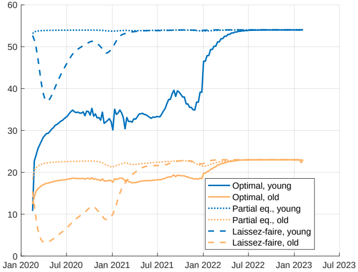
Optimal Lockdown

Planner chooses time series of lockdown taxes, separately by age, to maximize utilitarian welfare.

(a) Time tax rates



(b) Time outside



Time outside for young *lower*, but for old *higher* than laissez-faire.

▸ Zoom graph

Optimal Lockdown

		Optimal lockdown (1)	Benchmark lockdown (2)
% Deaths averted, rel. to no-lockdown	Young	97.95	50.38
	Old	96.73	43.18
	All	96.96	44.5
% Change in GDP, rel. to no-lockdown		-10.61	-5.55
CEV rel. to no-lockdown	Young	0.36	0.24
	Old	16.86	7.42

Optimal lockdown saves almost all lives, at sizable GDP loss.
Almost all welfare gains to the old.

Optimal Policy for Other Pandemics: Spanish Flu

- Spanish flu was another deadly pandemic.
- Lockdowns at the time much shorter and milder.
- Would more severe lockdowns have been better at the time?
- Many differences
  - Lowever income, no teleworking, younger, lower life expectancy, lower R_0, less steep CFR age gradient, no tests, longer expected vaccine time arrival
- We find: optimal lockdown for the young is laxer than for Covid.
- Main reason: laissez-faire death rate is higher for Spanish flu and age-gradient is flatter $\rightarrow$ more voluntary protection $\rightarrow$ less need for additional lockdowns.
- Paper: detailed decomposition of all the factors.

General lessons for future pandemics?

- Several viruses have the potential to cause a pandemic: Ebola, Sars-Cov1, MERS, even Tuberculosis.
- Yet, they are all quite different from each other in infectiousness and mortality.
  The next pandemic might be totally different yet.
- We study optimal lockdowns for combinations of R_0, CFR and age gradient and find:
  - Lockdowns should be strict if R_0 is high, and less so when only CFR is high.
  - CFR age gradient matters: if deadlier for the young $\rightarrow$ optimal lockdown is laxer.
  - Optimal lockdown depends on economic conditions:
    young societies, high income, easy WfH $\rightarrow$ less restrictive policy.
  - Optimal policies often avert almost all deaths, but not always the case.
  - Welfare gains from optimal policy can be very unevenly divided $\rightarrow$ explains perhaps political pressure of the working age population to ease restrictions during Covid.

Outline

Conclusion

- Econ-epi framework to study age heterogeneity and incomplete information
- Covid-19 application
- The elderly already protect themselves a lot in the laissez-faire equilibrium
- Optimal lockdown: controls Covid and let the old freer than under no-lockdown
- Lessons for other pandemics:
  - Laxer lockdowns during the Spanish flu made sense.
  - R_0 matters more than CFR, age gradient important too.
  - Economic conditions also relevant $\rightarrow$ implications for developing countries.

Value functions

- Infected agent (who knows it):

$$
\begin{aligned}
V_t(i,a) = \max_{c,x,n,v,\ell,d} & \, u(c, g(x,\ell), d) \\
& + \beta(a)\phi(0,a)W_{t+1}(r,a) \\
& + \beta(a)(1-\phi(0,a))\alpha(a)W_{t+1}(h,a) \\
& + \beta(a)(1-\phi(0,a))(1-\alpha(a))W_{t+1}(i,a)
\end{aligned} \tag{8}
$$

s.t. constraints

Value functions

- Agent in the fever state (uncertain):

$$V_t(f,a) = \max_{c,x,n,v,\ell,d} \frac{\Pi^*_{t-1}}{\Pi_{t-1} + \Pi^*_{t-1}} \tilde{V}_t(c,x,n,v,\ell,d,v;s,a) + \frac{\Pi_{t-1}}{\Pi_{t-1} + \Pi^*_{t-1}} \tilde{V}_t(c,x,n,v,\ell,d,v;i,a), \tag{9}$$

where $\tilde{V}_t(c,x,n,\ell,d,v;j,a)$ is the value of agent j in time t if making choices c, x, n, ℓ, d, v in t

Value functions

- Hospitalized agent:

$$V_t(h,a) = \beta(a)\left[\phi(1,a)W_{t+1}(r,a) + (1-\phi(1,a))(1-\delta(a))W_{t+1}(h,a)\right] \quad (10)$$

- Recovered agent:

$$V_t(r,a) = \max_{c,x,n,v,\ell,d} u(c, g(x,\ell), d) + \beta(a)W_{t+1}(r,a) \quad (11)$$

- We'll skip the laws of motion of aggregate distributions

Laws of motion of measures

- How you would expect them to be
- For example:

$$
\begin{aligned}
&M_{t+1}(s,a) \qquad (12)\\
&= M_t(s,a)\Delta(a)\left[1-\pi_f(n_t(s,a)+\ell_t(s,a),\Pi_t,\Pi_t^*)+\pi^*(n_t(s,a)+\ell_t(s,a),\Pi_t^*)\xi_t(a)\right]\\
&+ M_t(f_s,a)\Delta(a)\left[1-\pi_f(n_t(f,a)+\ell_t(f,a),\Pi_t,\Pi_t^*)+\pi^*(n_t(f,a)+\ell_t(f,a),\Pi_t^*)\xi_t(a)\right],
\end{aligned}
$$

where $\Delta(a)$ is the natural survival prob. and π_f is the prob. of catching Covid or the common cold

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Table: Calibration – Economic & Preference Parameters

Parameter	Value	Interpretation
	0.214	Fraction of old in population
ρ	-1.72	Elasticity of subst. bw leisure time and goods
θ	0.033	Production of leisure goods
γ	0.635	Rel. utility weight - leisure goods
λ	1.562	Rel. utility weight - leisure at home
$\tilde{\beta}$	$0.96^{1/52}$	Discount factor
w	1	Wage per unit of time
$\overline{w}$	0.214	Retirement income
$\Delta(y)$	0.9995	Weekly survival (natural causes), young
$\Delta(o)$	0.9985	Weekly survival (natural causes), old
ι_0	1.055	Parameter related to telework productivity
ι_1	0.960	Parameter related to telework productivity
b	15.63	Flow value of being alive

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Table: Calibration – Disease Parameters

Parameter	Value	Interpretation
α	1	Prob(hospitalization | no recovery from mild)
$\phi(0, y)$	0.988	Prob of recovering from mild Covid-19, young
$\phi(0, o)$	0.871	Prob of recovering from mild Covid-19, old
$\phi(1, y)$	0.284	Prob of recovering from hospitalization, young
$\phi(1, o)$	0.284	Prob of recovering from hospitalization, old
$\delta(y)$	0.090	Weekly death rate (among hospitalized), young
$\delta(o)$	0.921	Weekly death rate (among hospitalized), old
$\bar{\ell}_h$	0.158	Infections through the health care system
χ_t	1/78	Prob of vaccine arrival (average = 78 weeks)
Π^*	0.094	Weekly infectiousness of common cold/flu

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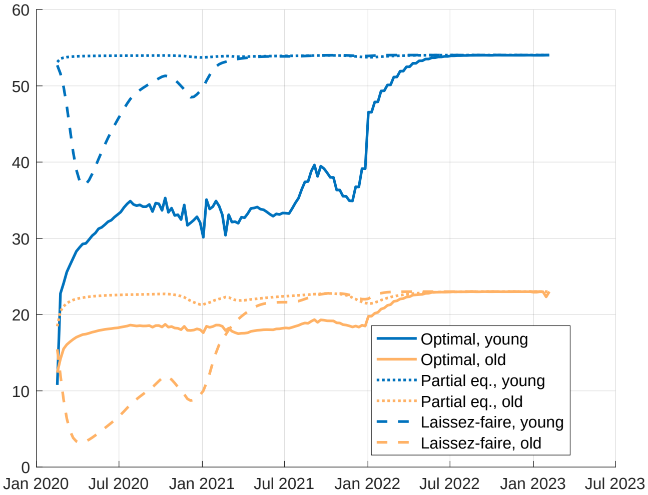
Figure: Time outside



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