The Effect of Large-Scale Anti-Contagion Policies on the Coronavirus (COVID-19) Pandemic

The Global Policy Laboratory | UC Berkeley

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HELP Workshop – May 1, 2020

Motivation

Currently, cost-benefit analysis of anti-contagion policies is almost impossible with existing information.

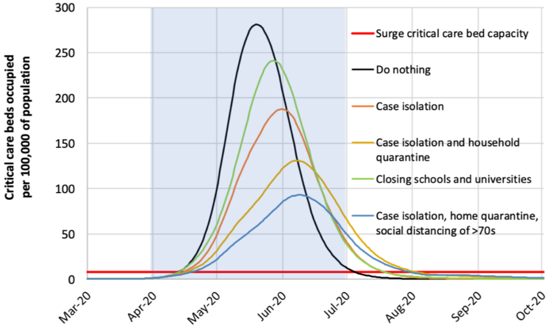
Costs of policies (e.g. stock market, unemployment) are salient and easily observed.

Benefits of policies (averted cases, lives not lost) cannot be directly observed.

Standard econometric approaches are ideally suited to measure these benefits.

Current understanding of benefits comes exclusively from forward-looking process-based epidemiological simulations.

These simulations are "structural" models that rely on numerous "deep" epidemiological parameters that are challenging to quantify.



The predicted impact that countermeasures could have on critical care bed use in Britain. Imperial College COVID-19 Response Team

Impacts of ongoing policies have not been directly measured.

Research Questions

Global Policy Lab breakfast meeting on March 13th:

1) Can we empirically measure the benefits of anti-contagion policies using available data from countries with early outbreaks?'

2) If so, which policies "work" and/or generate the greatest benefits?

Information can be useful to populations and decision-makers in remaining 180 countries where COVID-19 has been detected.

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(paper submitted on March 23rd)

Data Collection

Six Countries with early outbreaks and subnational data:
$\rightarrow$ **China, South Korea, Iran, Italy, France, USA**

Restrict dates to $>$10 confirmed cases, no policies lifted:
$\rightarrow$ **January 16** (China) — **April 6** (S. Korea, Italy, USA)

Daily subnational epidemiological data on confirmed **active cases** (China, S. Korea) or **cumulative cases**.

Data on documented **regime changes for diagnosis or testing** (country-level)

Subnational data on **deployment of anti-contagion policies**.

Types of anti-contagion policies

Policies are aggregated or hand-collected from a variety of sources (e.g. online databases, news articles):

- travel bans
- transit restrictions
- business closures
- quarantining positive cases
- lockdowns / home isolation
- emergency declarations
- expansions of paid sick leave
- school closure
- canceling events
- prohibiting religious gatherings
- work from home
- other social distancing measures (closing museums / libraries)

Policies are aggregated up (population weights) to administrative units of case data.

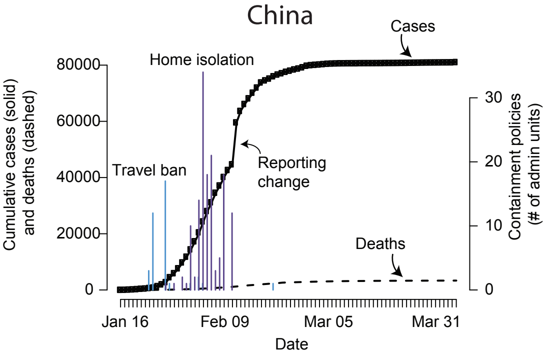
Policies are grouped based on similarity of objective (e.g. travel restrictions) or timing of deployment.

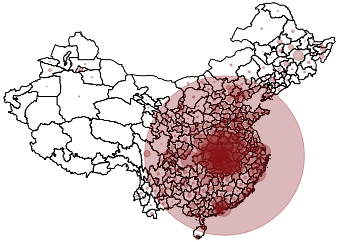
Number of unique anti-contagion policies in this study by administrative division

Country	Adm0	Adm1	Adm2	Adm3	Total
China	0	4	133	0	137
France	8	1	50	0	59
Iran	5	17	0	0	22
Italy	14	29	95	77	215
South Korea	20	39	0	0	59
United States	36	682	418	31	1167
Total	83	772	696	108	1659

Adm0 = country; Adm1 = state; Adm2 = county

Compiling new data: subnational cases + policies





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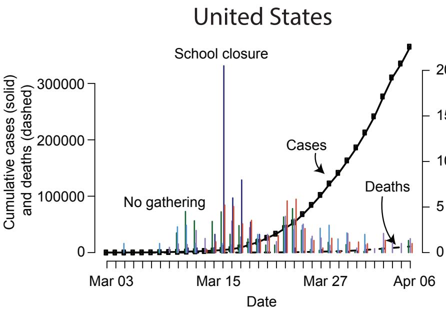

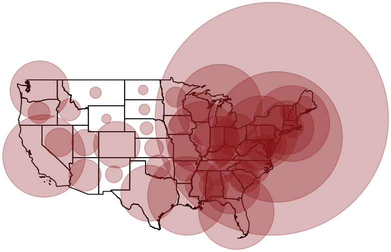

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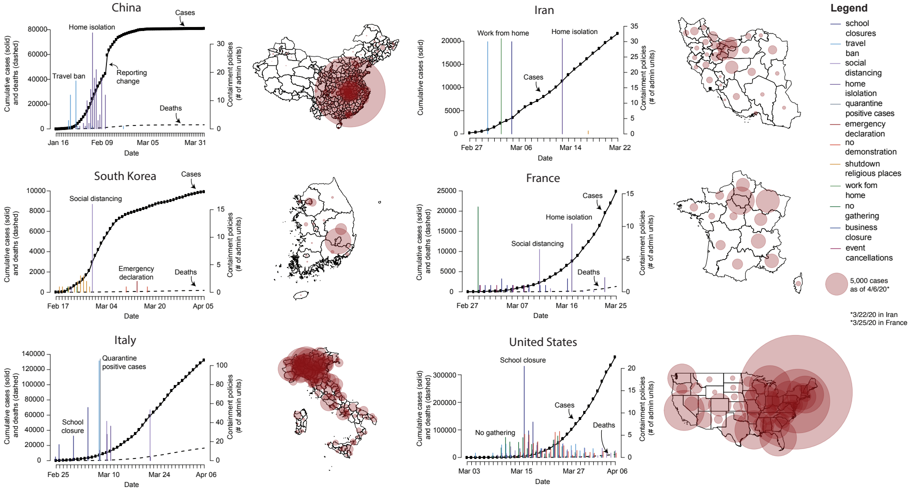

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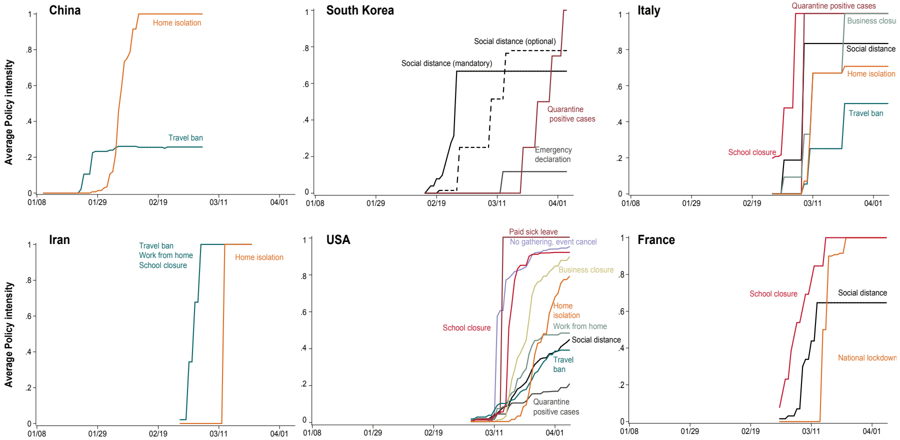
Summaries: national average policy intensity



All data public → globalpolicy.science/covid19

Model

In Susceptible-Infected-Recovered (SIR) disease model, the rate of change in infections early in an epidemic is

$$\frac{dI_t}{dt} = (S_t\beta - \gamma)I_t \underset{S_t \to 1}{=} (\beta - \gamma)I_t$$

I_t = infected individuals at time t
S_t = susceptible fraction of the population
β = transmission rate
γ = removal rate

Therefore, active infections grow exponentially in every time step:

$$\frac{I_{t_2}}{I_{t_1}} = e^{g_t \cdot (t_2 - t_1)} \tag{1}$$

where daily growth rate g_t is a function of behavior and policy.

Estimation

Estimate a separate panel growth regression for each country:

$$\underbrace{\log(I_{cit}) - \log(I_{ci,t-1})}_{\textit{daily growth rate } g_t} = \theta_{0,ci} + \delta_{ct} + \mu_{cit} + \sum_{p=1}^{P_c} (\theta_{cp} \cdot policy_{pcit}) + \epsilon_{cit}$$

I = number of infected individuals
θ_0 = subnational unit-fixed effects (e.g. state or city)
δ = day-of-week-fixed effects
μ = testing regime dummies
policy = dummy variable for enacted policies

Country c, subnational unit i, and day t.

Identification

Decisions to deploy policy are likely independent of growth rates or anticipation of growth rates.

$\rightarrow$ epidemiological guidance to decision-makers was explicit that growth rates are constant in the absence of policy.

In practice, policies are generally deployed in response to

- levels of cumulative cases (not growth rates)
- outbreaks in other locations
- other arbitrary events (e.g. closing businesses on a Monday or schools after Spring Break).

Is exponential growth a good assumption?

Exponential growth occurs when most of the population remains susceptible.

After correcting for estimated rates of case-detection (Russell et al., 2020), we compute:

- Susceptible fraction of population $> 95\%$ across 86% of administrative units across all six countries at end of sample.
- Minimum susceptible population in any of the administrative units in our sample is approximately 78.0% (Cremona, Italy).

$\rightarrow$ Much of sample would likely be in a regime of uninhibited exponential growth if policies were removed.

Under-reporting of cases?

Suppose each locality i reports only a fraction ψ_i of infections.

We observe $\tilde{I}_{it} = \psi_i I_{it}$ rather an actual infections I_{it}.

$$\begin{aligned}\log(\tilde{I}_{it}) - \log(\tilde{I}_{i,t-1}) &= \log(\psi_i I_{it}) - \log(\psi_i I_{i,t-1}) \\ &= \log(\psi_i) - \log(\psi_i) + \log(I_{it}) - \log(I_{i,t-1}) \\ &= \log(I_{it}) - \log(I_{i,t-1}) = g_{it}\end{aligned}$$

$\rightarrow$ robust to systematic, time-invariant, location-specific under-reporting.

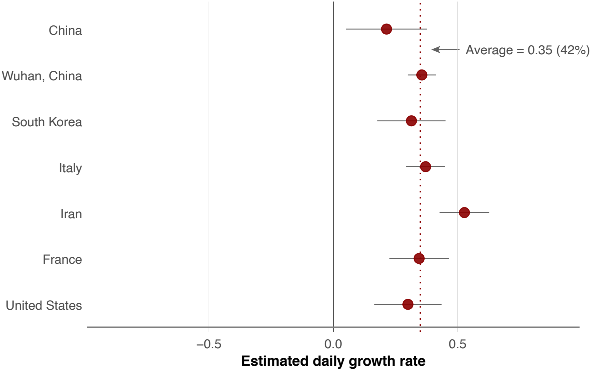
If there are trends in case-detection:

$$\log(\tilde{I}_{it}) - \log(\tilde{I}_{i,t-1}) = \underbrace{\log(\psi_{it}) - \log(\psi_{i,t-1})}_{\textit{growth rate of \% cases detected}} + g_{it}$$

Using time-varying case detection rates, we estimate this bias may be roughly 0.022 on average (6.2% of baseline).

"No policy" growth rates

Infection growth rate without policy

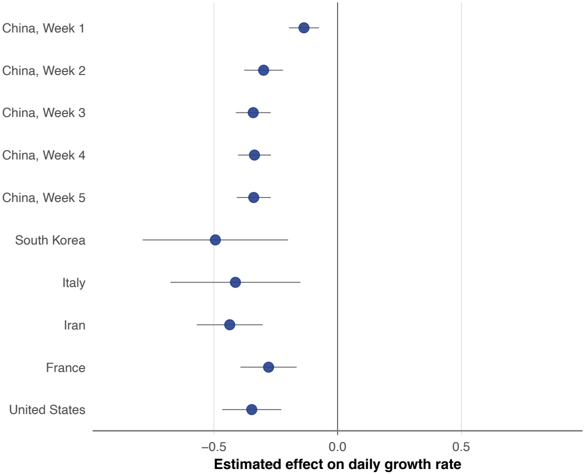


	Effect size (Δlog per day)	As percent growth (% per day)
China	0.21 (0.05, 0.38)	23.86
Wuhan, China	0.36 (0.3, 0.41)	42.76
South Korea	0.31 (0.18, 0.45)	36.89
Italy	0.37 (0.29, 0.45)	45.21
Iran	0.53 (0.43, 0.63)	69.38
France	0.34 (0.23, 0.46)	41.2
United States	0.3 (0.16, 0.44)	34.99

(These are mostly unobserved, actual infection growth is confounded by policy.)

Effect if all available policies are fully deployed

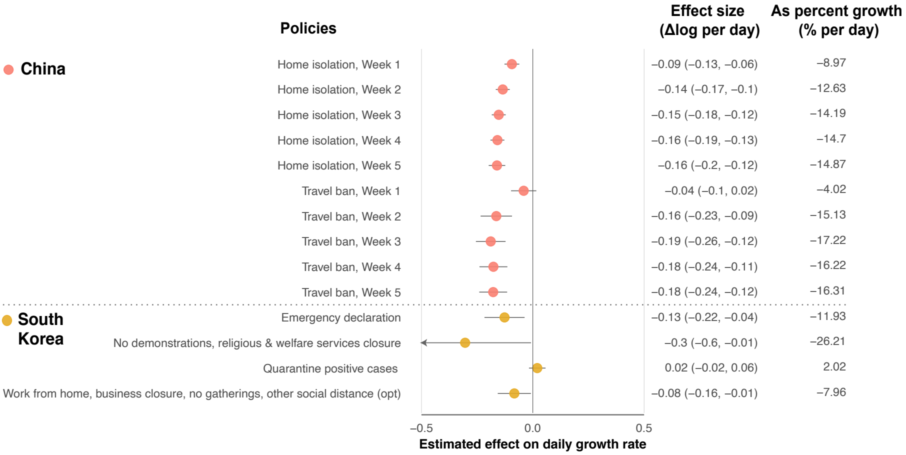
Effect of all policies combined



	Effect size (Δlog per day)	As percent growth (% per day)
China, Week 1	−0.14 (−0.2, −0.08)	−12.72
China, Week 2	−0.3 (−0.38, −0.22)	−25.84
China, Week 3	−0.34 (−0.41, −0.27)	−28.89
China, Week 4	−0.34 (−0.4, −0.27)	−28.54
China, Week 5	−0.34 (−0.41, −0.27)	−28.75
South Korea	−0.49 (−0.79, −0.2)	−38.98
Italy	−0.41 (−0.64, −0.18)	−33.57
Iran	−0.44 (−0.57, −0.3)	−35.34
France	−0.28 (−0.39, −0.17)	−24.35
United States	−0.35 (−0.47, −0.23)	−29.32

(Few locations deploy all policies in our sample.)

Effect of individual policies



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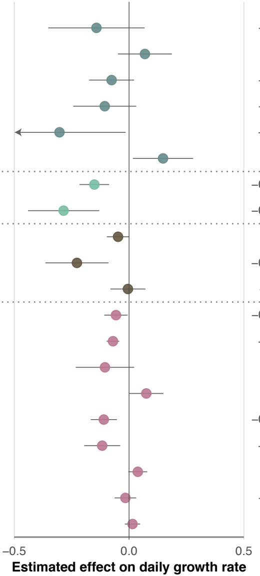
Effect of individual policies

Country	Policies	Effect size (Δlog per day)	As percent growth (% per day)
Italy	Business closure	−0.14 (−0.35, 0.07)	−13.24
	Home isolation	0.07 (−0.05, 0.19)	7.14
	Quarantine positive cases	−0.08 (−0.17, 0.02)	−7.32
	School closure	−0.11 (−0.24, 0.03)	−10.06
	Travel ban, transit suspension	−0.3 (−0.59, −0.01)	−26.14
	Work from home, no gatherings, other social distance	0.15 (0.02, 0.28)	15.95
Iran	Home isolation	−0.15 (−0.22, −0.09)	−14.02
	School closure, travel ban (opt), work from home	−0.28 (−0.44, −0.13)	−24.8
France	Business closure, home isolation	−0.05 (−0.1, 0)	−4.69
	Event cancellations, no gatherings, other social distance	−0.23 (−0.36, −0.09)	−20.31
	School closure	−0.01 (−0.08, 0.07)	−0.5
United States	Business closure	−0.06 (−0.11, −0.01)	−5.54
	Home isolation	−0.07 (−0.1, −0.04)	−6.76
	No gatherings, event cancellations	−0.1 (−0.23, 0.02)	−9.97
	Paid sick leave	0.08 (0, 0.15)	7.79
	Quarantine positive cases	−0.11 (−0.17, −0.05)	−10.42
	Religious closure, other social distance	−0.12 (−0.2, −0.04)	−11.04
	School closure	0.04 (0, 0.08)	3.87
	Travel ban, transit suspension	−0.02 (−0.06, 0.03)	−1.59
	Work from home	0.02 (−0.02, 0.05)	1.51



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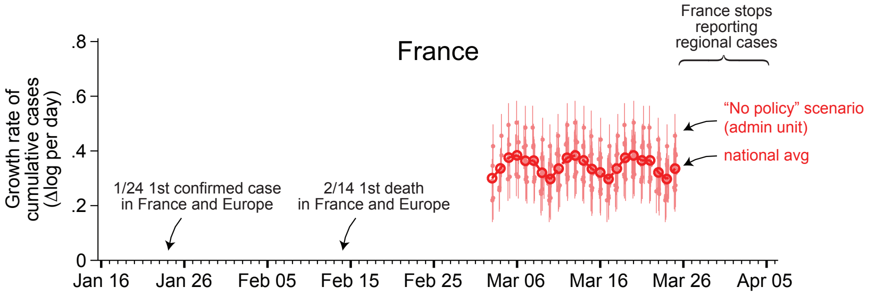
Predicting counterfactual infection growth rates



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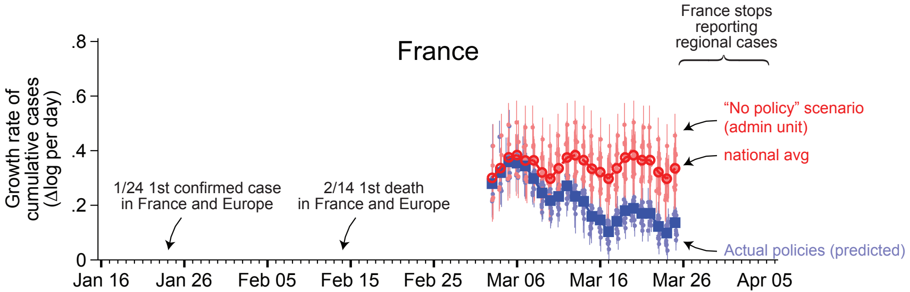

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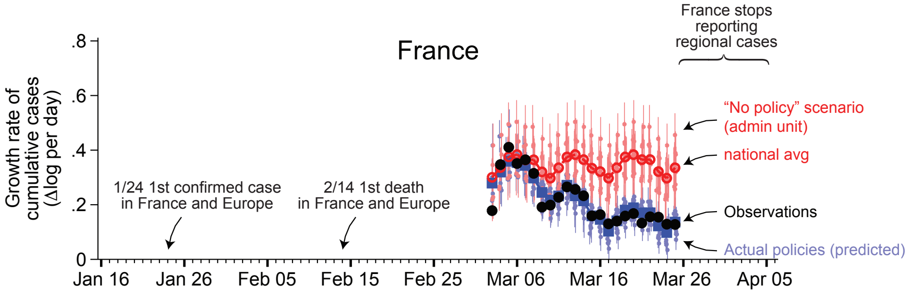
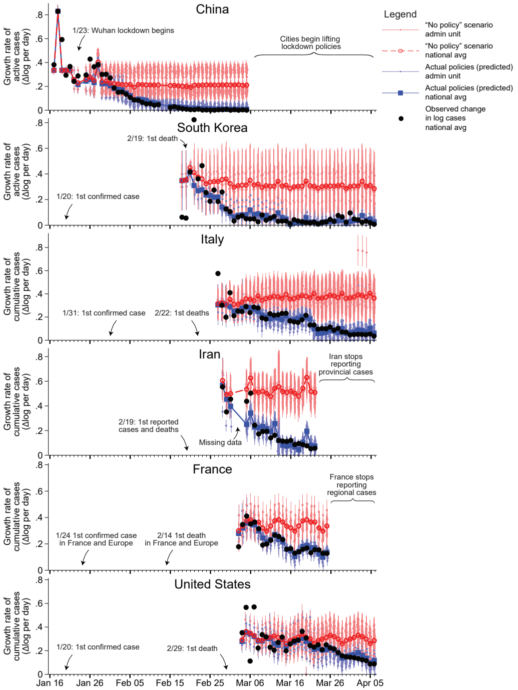




China
South Korea
Italy
Iran
France
United States
Growth rate of active cases (Δlog per day)
Growth rate of cumulative cases (Δlog per day)
1/23: Wuhan lockdown begins
Cities begin lifting lockdown policies
2/19: 1st death
1/20: 1st confirmed case
1/31: 1st confirmed case
2/22: 1st deaths
2/19: 1st reported cases and deaths
Missing data
Iran stops reporting provincial cases
1/24 1st confirmed case in France and Europe
2/14 1st death in France and Europe
France stops reporting regional cases
2/29: 1st death
Jan 16
Jan 26
Feb 05
Feb 15
Feb 25
Mar 06
Mar 16
Mar 26
Apr 05
Legend
"No policy" scenario admin unit
"No policy" scenario national avg
Actual policies (predicted) admin unit
Actual policies (predicted) national avg
Observed change in log cases national avg

Average total effect of anti-contagion policies

Without policy, daily infection growth rate = $\underline{+0.35\ (42\%)\ \text{per day}}$
$\rightarrow$ doubling every $\underline{2\ \text{days}}$.

Impacts of policy depend on timing and duration of deployment.

In our sample, we estimate all anti-contagion policies combined slowed average daily growth rate of infections:

China −0.156 (±0.015**) per day**

S Korea: −0.248 (±0.089**) per day**

Italy: −0.241 (±0.068**) per day**

Iran: −0.362 (±0.069**) per day**

France: −0.139 (±0.038**) per day**

USA: −0.092 (±0.033**) per day**

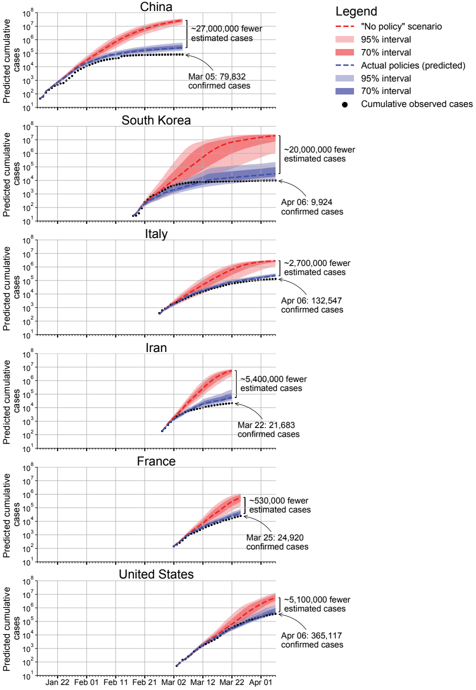
Cumulative effect on total cases

We want to understand scale of total benefit from deployed policies.

$\rightarrow$ Integrate growth rates to compute total infections averted.

Challenge: As more infections occur, growth rate natural slows because fewer individuals to infect.

Solution: Link results to SIR / SEIR model to adjust for changing susceptible population (including undetected cases).



China
South Korea
Italy
Iran
France
United States
Predicted cumulative cases
~27,000,000 fewer estimated cases
Mar 05: 79,832 confirmed cases
~20,000,000 fewer estimated cases
Apr 06: 9,924 confirmed cases
~2,700,000 fewer estimated cases
Apr 06: 132,547 confirmed cases
~5,400,000 fewer estimated cases
Mar 22: 21,683 confirmed cases
~530,000 fewer estimated cases
Mar 25: 24,920 confirmed cases
~5,100,000 fewer estimated cases
Apr 06: 365,117 confirmed cases
Jan 22
Feb 01
Feb 11
Feb 21
Mar 02
Mar 12
Mar 22
Apr 01
Legend
"No policy" scenario
95% interval
70% interval
Actual policies (predicted)
95% interval
70% interval
Cumulative observed cases

Benefits of policy: est. cases delayed or avoided

Country	End date	Cumulative "confirmed" cases delays / avoided
China	3-05	26,988,000
South Korea	4-06	20,149,000
Italy	4-06	2,684,000
Iran	3-22	5,358,000
France	3-25	532,000
United States	4-06	5,108,000
Total		60,819,000

Sensitivity tests using Susceptible-Exposed-Infected-Removed (SEIR) model: 57–65 million confirmed cases averted (central est).

Conclusions

- Without policy, daily infection growth rate = +0.35 (42%) per day → doubling every 2 days.
- Current policy packages are effective at dramatically slowing growth rate if fully deployed.
- Ranking policies is more difficult with currently available data, but possible in some countries.
- It takes roughly 3 weeks for full effects to be observed.
- Existing policies are generating large benefits (e.g. without policy: 339× current cumulative infections in China, 15× in the US)
- Likely delayed / avoided on the order of 60M confirmed infections across six countries during our sample (ended April 6).