

# Causal Impact of Masks, Policies, Behavior on Early Covid-19 Pandemic in the U.S.

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- What is the impact of various policies adopted by the US states on the spread of COVID-19?
- Mandatory face mask policy?
- How do people adjust their behavior to policies and new information on higher transmission risks?

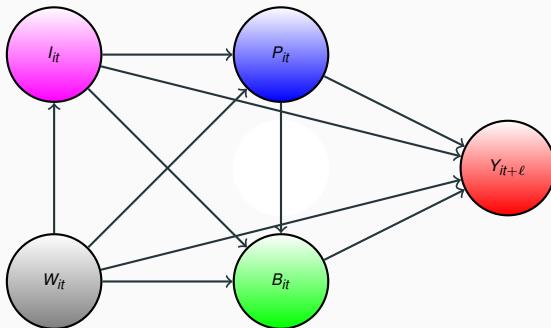
# Literature

- The impact of non pharmaceutical interventions on Covid-19 cases: Hsiang et al. (2020), Courtemanche et al. (2020), Avery et al. (2020) for review.
- The impact of social distancing policies on behavior in the US is mixed: Abouk and Heydari (2020), Maloney and Taskin (2020), Gupta et al. (2020), Andersen (2020)
- Pei et al. (2020) provides simulation of implementing all policies 1-2 weeks earlier.
- Model simulations by epidemiologists (e.g., Ferguson et al., 2020). Substantial uncertainty in parameters (Avery et al., 2020; Stock, 2020)
- Fernández-Villaverde and Jones (2020) estimate a SIRD model that captures feedback from daily deaths to future behavior and infections.
- No existing experimental evidence for face mask. Our work is complementary to the medical observational evidence reviewed in Greenhalgh et al. (2020) and Howard et al. (2020), the laboratory findings of Hou et al. (2020), as well as the findings in Abaluck et al. (2020), Mitze et al. (2020), and Miyazawa and Kaneko (2020).

## Contributions of this paper

1. The causal framework on how the Covid-19 spread is dynamically determined by policies and human behavior.
  - Direct vs. indirect effect of policies.
  - People voluntarily adjust their behavior in response to new information on reported cases/deaths.
  - Dynamic feedback.
2. Regression analysis on how the growth rates of Covid-19 cases/deaths are determined by policies and behavior using the US state-level data.
3. Counterfactual experiments
  - What if mandatory face mask policy had been adopted everywhere on March 14th?
  - What if no stay-at-home (shelter-in-place) orders?

# Causal Model



- $Y_{it+l}$ : the *forward* growth rate of cases/deaths
- $P_{it}$ : the lagged policies (e.g., mandatory face mask policy)
- $B_{it}$ : the lagged behavior variables (Google mobility measures)
- $I_{it}$ : information on transmission risks (past cases and deaths)
- $W_{it}$ : confounders (state-level characteristics, month dummies)

# Structural Equation Model and Orthogonality Restrictions

$$Y_{it+\ell} = \alpha' B_{it} + \pi' P_{it} + \mu' I_{it} + \delta_Y' W_{it} + \varepsilon_{it}^Y, \quad \varepsilon_{it}^Y \perp B_{it}, P_{it}, I_{it}, W_{it} \\ \text{(BPI} \rightarrow \text{Y)}$$

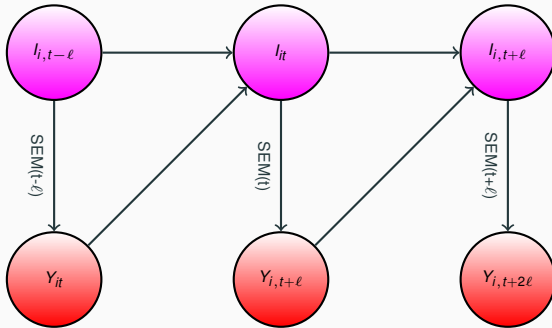
$$B_{it} = \beta' P_{it} + \gamma' I_{it} + \delta_B' W_{it} + \varepsilon_{it}^b, \quad \varepsilon_{it}^b \perp P_{it}, I_{it}, W_{it} \\ \text{(PI} \rightarrow \text{B)}$$

and

$$Y_{it+\ell} = (\pi' + \alpha' \beta') P_{it} + (\mu' + \alpha' \gamma') I_{it} + \bar{\delta}' W_{it} + \bar{\varepsilon}_{it}, \quad \bar{\varepsilon}_{it} \perp P_{it}, I_{it}, W_{it}. \\ \text{(PI} \rightarrow \text{Y)}$$

- $\pi'$ : direct effect of policy.
- $\alpha' \beta'$ : indirect effect of policy on infection through behavior.

# Dynamic feedback



$$I_{it} = \left( Y_{it}, \sum_{m=0}^{t/\ell} Y_{i,t-\ell m} \right)' = (\text{lagged case growth, lagged cases})$$

# Susceptible-Infectious-Recovered (SIR) Model with testing

SIR Model with confirmed cases  $\dot{C}(t)$  and testing  $\tau(t)$ :

$$\dot{S}(t) = -\frac{S(t)}{N}\beta(t)\mathcal{I}(t), \quad \dot{\mathcal{I}}(t) = \frac{S(t)}{N}\beta(t)\mathcal{I}(t) - \gamma\mathcal{I}(t),$$

$$\dot{R}(t) = (1 - \kappa)\gamma\mathcal{I}(t), \quad \dot{D}(t) = \kappa\gamma\mathcal{I}(t), \quad \dot{C}(t) = \tau(t)\mathcal{I}(t).$$

Differentiating  $\dot{C}(t) = \tau(t)\mathcal{I}(t)$  and  $\dot{D}(t) = \kappa\gamma\mathcal{I}(t)$ ,

$$\frac{\ddot{C}(t)}{\dot{C}(t)} = \frac{S(t)}{N}\beta(t) - \gamma + \frac{\dot{\tau}(t)}{\tau(t)},$$

$$\frac{\ddot{D}(t)}{\dot{D}(t)} = \frac{S(t)}{N}\beta(t) - \gamma.$$



# SIR Model and Empirical Specification

Discrete-time analogue with  $\frac{S(t)}{N} \approx 1$  and

$$\underbrace{\beta(t)}_{\text{infection rate}} \approx X'_{i,t-\ell} \theta + \epsilon_{it}$$

with

$X_{it}$  = policy and behavior variables

$\Rightarrow$

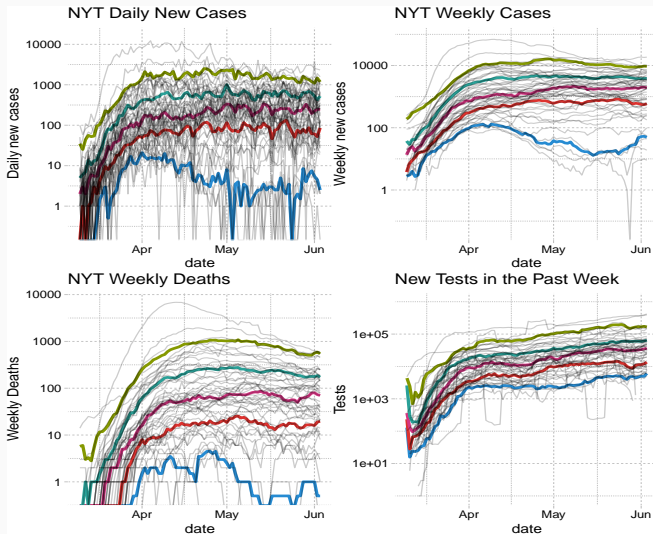
$$\underbrace{\Delta \log \Delta C_{it}}_{\text{growth rate of cases}} = X'_{i,t-14} \theta + \epsilon_{it} - \gamma + \delta_T \underbrace{\Delta \log(T)_{it}}_{\text{growth rate of tests}}$$

$$\underbrace{\Delta \log \Delta D_{it}}_{\text{growth rate of deaths}} = X'_{i,t-21} \theta + \epsilon_{it} - \gamma$$

- Data Period: from March 7 to June 3.
- **Daily cases and deaths**: NYT, JHU, Covid Tracking Project.
- The number of tests: Covid Tracking Project
- **US state policies**: Raifman et al. (2020).
- **Behavior variables**: “Transit stations,” “Workplaces,” “Grocery & pharmacy,” and “Retail & recreation” from Google Mobility Reports.

We use 7 days moving averages of all variables

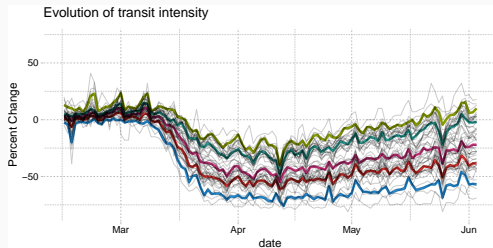
# Daily/Weekly Cases, Weekly Deaths, and Weekly Tests



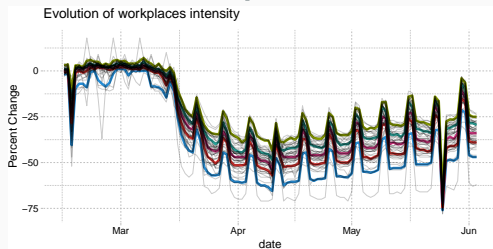
Thin gray lines are the log of cases, death, and tests in each state and date.  
Thicker colored lines are their quantiles conditional on date.

# The Evolution of “Transit stations” and “Workplaces”

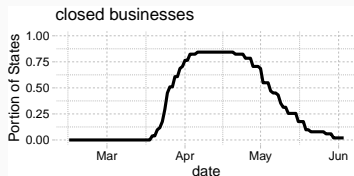
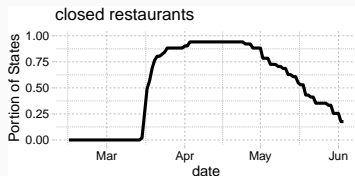
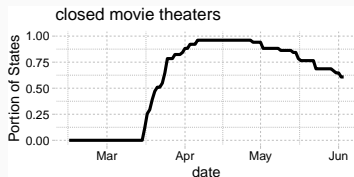
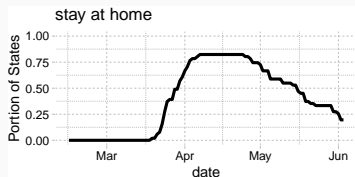
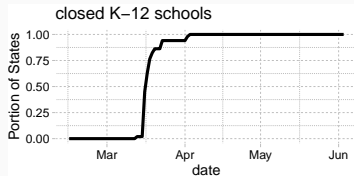
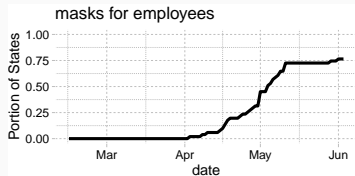
## Transit



## Workplaces



# Portion of states with each policy

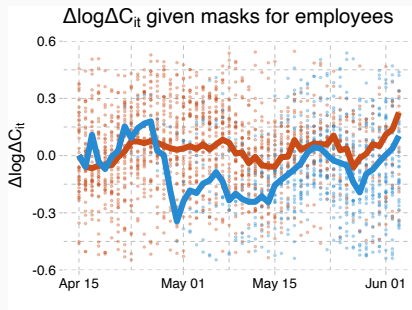


# Correlations among policy and behavior variables

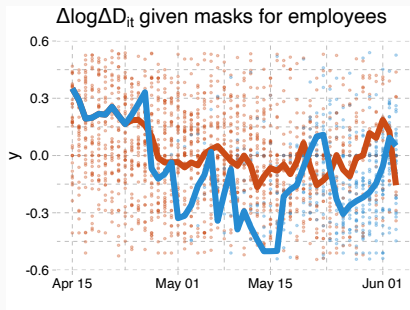
	workplaces	retail	grocery	transit	masks for employees	closed K-12 schools	stay at home	closed movie theaters	closed restaurants	closed businesses
workplaces	1.00									
retail	0.94	1.00								
grocery	0.75	0.82	1.00							
transit	0.90	0.92	0.83	1.00						
masks for employees	-0.32	-0.19	-0.16	-0.30	1.00					
closed K-12 schools	-0.92	-0.81	-0.58	-0.75	0.46	1.00				
stay at home	-0.70	-0.69	-0.71	-0.72	0.31	0.65	1.00			
closed movie theaters	-0.82	-0.77	-0.65	-0.72	0.40	0.85	0.75	1.00		
closed restaurants	-0.79	-0.83	-0.69	-0.77	0.26	0.77	0.74	0.84	1.00	
closed businesses	-0.66	-0.68	-0.68	-0.66	0.12	0.59	0.77	0.69	0.73	1.00

Each off-diagonal entry reports a correlation coefficient of a pair of policy and behavior variables.

# Case and death growth conditional on Mask Mandates



**Case Growth**



**Death Growth**

# Regression Analysis

$$Y_{it+\ell} = \alpha' B_{it} + \pi' P_{it} + \mu' I_{it} + \delta_Y' W_{it} + \varepsilon_{it}^Y \quad (\text{BPI} \rightarrow Y)$$

$$B_{it}^j = \beta' P_{it} + \gamma' I_{it} + \delta_B' W_{it} + \varepsilon_{it}^b \quad (\text{PI} \rightarrow \text{B})$$

$$Y_{it+\ell} = (\pi' + \alpha' \beta') P_{it} + (\mu' + \alpha' \gamma') I_{it} + \bar{\delta}' W_{it} + \bar{\varepsilon}_{it}. \quad (\text{PI} \rightarrow Y)$$

- $Y_{it+\ell}$ : the forward growth rate of cases or deaths
- $B_{it}^j$ : “Transit,” “Workplaces” “Grocery,” and “Retail”
- $P_{it}$ : various policies lagged by 14 or 21 days
- $I_{it}$ : past cases/deaths, national-level cases/deaths etc.
- $W_{it}$ : state-level characteristics, month dummies, and their interactions.



# The Effect of Policies and Information on Behavior (PI → B)

	<i>Dependent variable:</i>			
	Workplaces	Transit	Workplaces	Transit
	(1)	(2)	(3)	(4)
Mask for Employees	0.023* (0.012)	0.015 (0.025)	0.005 (0.008)	-0.010 (0.023)
School Closures	-0.196*** (0.030)	-0.243*** (0.050)	-0.044*** (0.013)	-0.047 (0.041)
Stay-at-Home	-0.028** (0.013)	-0.062** (0.028)	-0.034*** (0.011)	-0.074*** (0.028)
Business Closures	-0.081*** (0.017)	-0.080** (0.038)	-0.049*** (0.012)	-0.042 (0.036)
$\sum_j \text{Policy}_j$	-0.282*** (0.041)	-0.371*** (0.078)	-0.122*** (0.022)	-0.172*** (0.060)
$\Delta \log \Delta C_{it}$	0.015*** (0.003)	0.014*** (0.005)	0.017*** (0.002)	0.020*** (0.005)
$\log \Delta C_{it}$	-0.024*** (0.005)	-0.018* (0.010)	-0.005 (0.004)	0.004 (0.011)
$\Delta \log \Delta C_{it} \cdot \text{national}$			-0.033*** (0.005)	-0.053*** (0.012)
$\log \Delta C_{it} \cdot \text{national}$			-0.072*** (0.004)	-0.091*** (0.012)

Other policies include closures of movie theaters, restaurants, and non-essential businesses. State characteristics, month dummies, and their interactions are included.

# The Direct Effect of Policies, Behavior, and Information on Case Growth ( $BPI \rightarrow Y$ )

	Dependent variable: $\Delta \log \Delta C_{it}$			
	(1)	(2)	(3)	(4)
lag(masks for employees, 14)	-0.090*** (0.031)	-0.091*** (0.032)	-0.100*** (0.029)	-0.100*** (0.030)
lag(closed K-12 schools, 14)	-0.074 (0.080)	-0.083 (0.090)	0.043 (0.096)	0.031 (0.103)
	$\vdots$	$\vdots$	$\vdots$	$\vdots$
lag(workplaces, 14)	1.055* (0.543)	1.042* (0.556)	0.391 (0.610)	0.355 (0.618)
lag(retail, 14)	0.594* (0.303)	0.611** (0.309)	0.316 (0.316)	0.342 (0.317)
lag(grocery, 14)	-0.471* (0.284)	-0.478* (0.288)	-0.259 (0.282)	-0.266 (0.284)
lag(transit, 14)	0.347 (0.258)	0.339 (0.268)	0.355 (0.247)	0.339 (0.253)
$\sum_k w_k \text{Behavior}_k$	-0.804*** (0.140)	-0.801*** (0.140)	-0.425*** (0.157)	-0.413*** (0.160)
lag( $\Delta \log \Delta C_{it}$ , 14)	0.015 (0.026)	0.015 (0.025)	0.024 (0.028)	0.024 (0.028)
lag( $\log \Delta C_{it}$ , 14)	-0.105*** (0.019)	-0.105*** (0.019)	-0.088*** (0.021)	-0.087*** (0.021)
lag( $\Delta \log \Delta C_{it}$ .national, 14)			-0.095** (0.042)	-0.095** (0.043)
lag( $\log \Delta C_{it}$ .national, 14)			-0.177*** (0.049)	-0.180*** (0.050)
$\Delta \log T_{it}$	0.152*** (0.043)	0.153*** (0.043)	0.155*** (0.042)	0.156*** (0.041)

# Direct and Indirect Policy Effects for Case Regression

## Case Growth Regression without national case variables

	PI→B Coef. & PBI→Y Coef.			PI→Y Coef.	Average	Difference (over-id test)
	Direct $\pi'$	Indirect $\alpha' \beta'$	Total $\pi' + \alpha' \beta'$	Total $\pi' + \alpha' \beta'$	Total $\pi' + \alpha' \beta'$	
Mask for Employees	-0.096*** (0.030)	— (0.030)	-0.096*** (0.030)	-0.083** (0.039)	-0.089*** (0.032)	-0.013 (0.025)
School Closures	-0.073 (0.078)	-0.364*** (0.094)	-0.436*** (0.119)	-0.226** (0.092)	-0.331*** (0.102)	-0.210*** (0.056)
Stay-at-Home	-0.053 (0.052)	-0.032 (0.028)	-0.085 (0.058)	-0.127** (0.057)	-0.106* (0.057)	0.042** (0.020)
Business Closures	— (0.042)	-0.157*** (0.042)	-0.157*** (0.042)	-0.076 (0.066)	-0.117** (0.048)	-0.081 (0.054)
⋮	⋮	⋮	⋮	⋮	⋮	⋮
$\sum_j \text{Policy}_j$	-0.221** (0.108)	-0.553*** (0.124)	-0.774*** (0.166)	-0.512*** (0.151)	-0.643*** (0.156)	-0.262*** (0.061)

State characteristics, month dummies, and their interactions are included.

# Direct and Indirect Policy Effects for Case Regression

## Case Growth Regression with national case variables

	PI→B Coef. & PBI→Y Coef.			PI→Y Coef.	Average	Difference
	Direct	Indirect	Total	Total	Total	(over-id test)
	$\pi'$	$\alpha' \beta'$	$\pi' + \alpha' \beta'$	$\pi' + \alpha' \beta'$	$\pi' + \alpha' \beta'$	
Mask for Employees	-0.105*** (0.027)	—	-0.105*** (0.027)	-0.103*** (0.031)	-0.104*** (0.028)	-0.001 (0.016)
School Closures	0.045 (0.092)	-0.022 (0.034)	0.023 (0.101)	0.029 (0.099)	0.026 (0.100)	-0.007 (0.015)
Stay-at-Home	-0.071 (0.052)	-0.033* (0.019)	-0.104* (0.056)	-0.115** (0.052)	-0.110** (0.053)	0.011 (0.017)
Business closures	— (0.024)	-0.038 (0.024)	-0.038 (0.024)	-0.001 (0.061)	-0.019 (0.038)	-0.038 (0.054)
⋮	⋮	⋮	⋮	⋮	⋮	⋮
$\sum_j \text{Policy}_j$	-0.131 (0.123)	-0.094* (0.049)	-0.225* (0.134)	-0.190 (0.155)	-0.207 (0.143)	-0.035 (0.047)

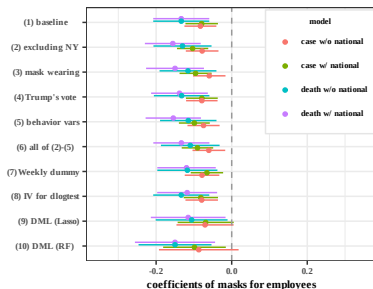
Other policies include closures of movie theaters, restaurants, and non-essential businesses. State characteristics, month dummies, and their interactions are included.

# Sensitivity Analysis

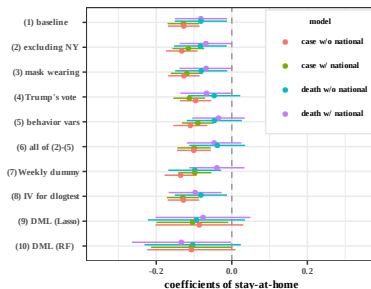
- (1) Baseline
- (2) Exclude the state of New York
- (3) Add % of people wearing masks in March and April
- (4) Add the log of Trump's vote share in 2016
- (5) Add past behavior variables as information
- (6) All of (2)-(5)
- (7) Add weekly dummies
- (8) Instrumenting  $\Delta \log T_{it}$  with one week lagged log value.
- (9) Double Machine Learning (DML) with Lasso in (3)-(5).
- (10) DML with Random Forest in (3)-(5).
  - Fixed effects + weekly dummies
  - Alternative Timing assumption ( $\ell = 10$  for cases and  $\ell = 23$  for deaths) on all of the above.

# Sensitivity Analysis: Mask Mandates and Stay-at-Home

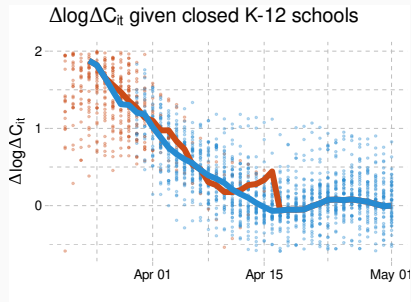
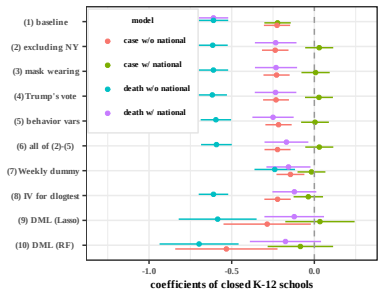
## Mask Mandates



## Stay-at-Home Orders



# Sensitivity Analysis: School Closures

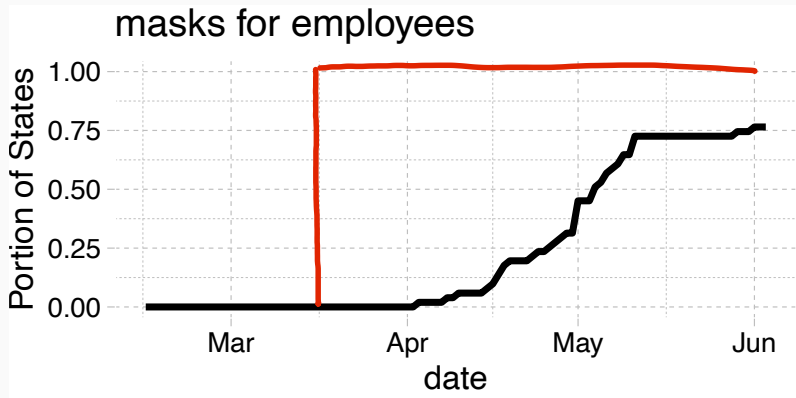


# Fixed Effects Estimator (State-level + Weekly FE)

	<i>Dependent variable:</i>	
	$\Delta \log \Delta C_{it}$	
	FE	FE + BC
lag(masks for employees, 14)	−0.103** (0.044)	−0.271*** (0.075)
lag(closed K-12 schools, 14)	−0.023 (0.060)	0.085 (0.098)
lag(stay at home, 14)	−0.123** (0.051)	−0.088 (0.068)
lag(business closure policies, 14)	−0.080 (0.076)	−0.162* (0.086)
lag( $\Delta \log \Delta C_{it}$ , 14)	0.063** (0.029)	0.079*** (0.026)
lag( $\log \Delta C_{it}$ , 14)	−0.216*** (0.020)	−0.185*** (0.032)
$\Delta \log T_{it}$	0.116*** (0.042)	0.116*** (0.042)
Observations	3,825	3,825
R <sup>2</sup>	0.782	0.782

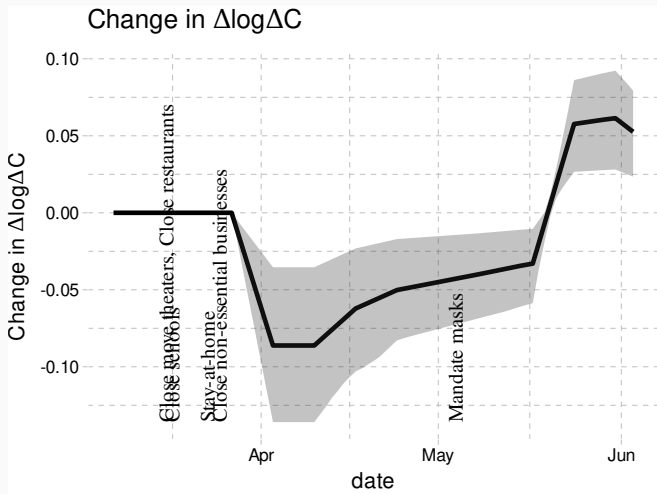


# Counterfactual Experiment of Mandating Masks on March 14th in all US states



# Counterfactual Effect of Mandating Masks on March 14th in Washington State

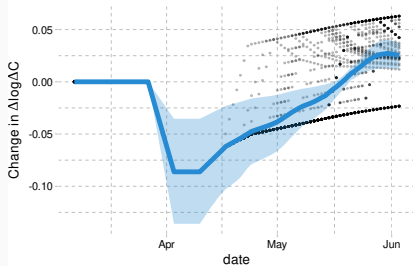
## Change in Case Growth Rates



# Counterfactual Effect of Nationally Mandating Masks on March 14th in the U.S.

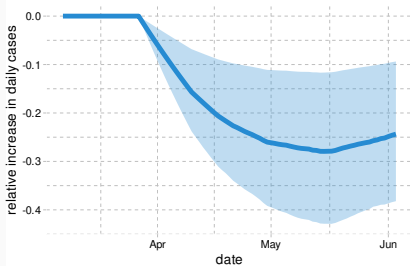
## Change in Case Growth

Effect of mandating masks on March 14th on case growth



## Relative Decrease in Cases

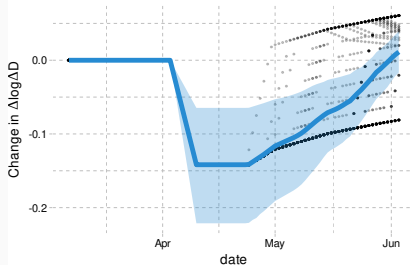
Relative effect of mandating masks on March 14th



# Counterfactual Effect of Nationally Mandating Masks on March 14th in the U.S.

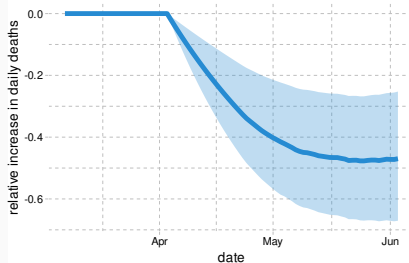
## Change in Death Growth

Effect of mandating masks on March 14th on death growth



## Relative Decrease in Deaths

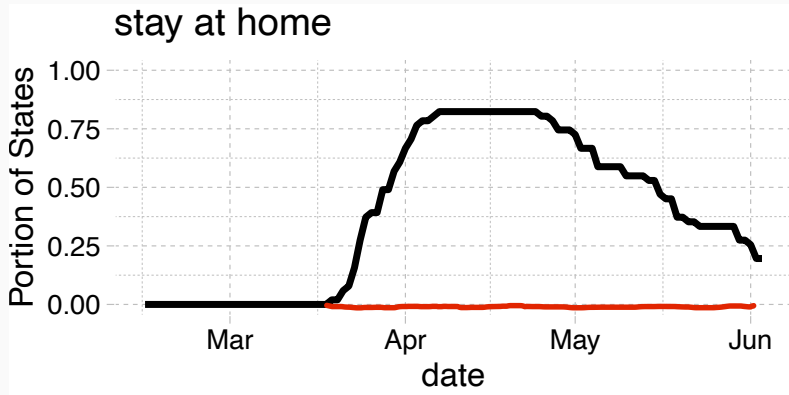
Relative effect of mandating masks on March 14th



19 to 47 percent less deaths nationally by the end of May

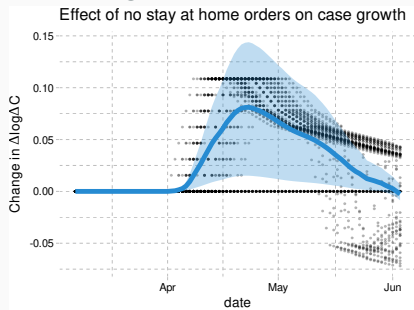
⇒ 19,000 to 47,000 saved lives!!

# Counterfactual Experiment of No Stay-at-Home Orders in the U.S.

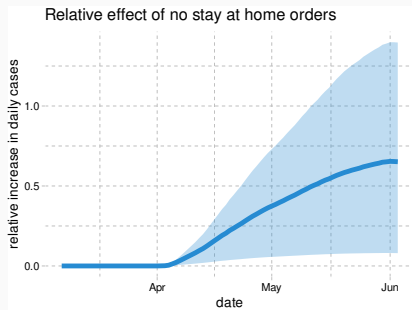


# Counterfactual Effect of No Stay-at-Home Orders in the U.S.

## Change in Case Growth



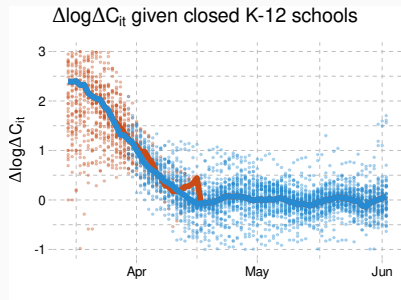
## Relative Increase in Cases



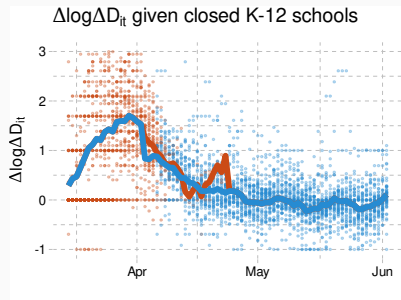
Cases would have been larger by 17 to 78 percent

⇒ 0.34 to 1.56 million more infections

# Case and death growth conditional on School Closures



**Case Growth**



**Death Growth**

The effect of school closures is not well identified.

## Conclusion

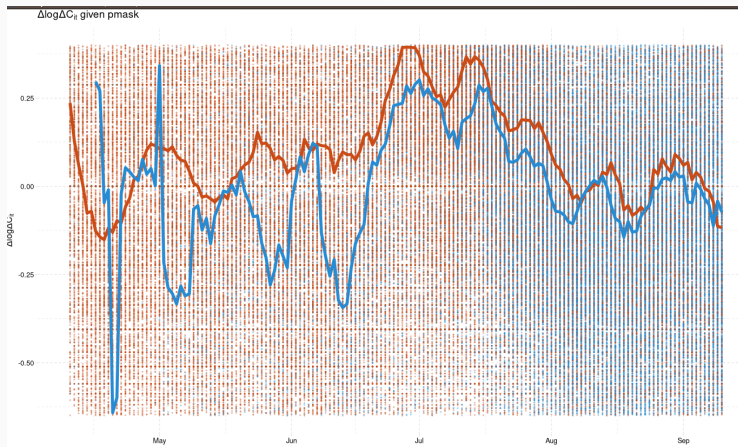
- A useful framework to estimate the roles of policies and information on determining the spread of Covid-19.
- If US-wide mask mandates had been adopted on March 14th, as much as 19,000 to 47,000 lives could have been saved by the end of May.
- Not having implemented Stay-at-Home Orders would have lead to 17% to 78% increase in cases.



## Conclusion

- Some evidence that people voluntarily reduce their mobility in response to a higher number of cases and deaths.
- There is much ambiguity related to the total effect of policies vs voluntary behavior, which can not be identified well from the US state-level data.
- Closure of schools has potentially large effects via behavior, keeping people at home, but school policy has almost no cross-sectional variation.

# County-level analysis



- Mask mandate matters!
- The effect of mandatory masks seems to get smaller over time, perhaps because more people voluntarily wear mask now.

## References

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