Are stay-at-home orders more difficult to follow for low-income groups? [§]

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Abstract:
In response to the COVID-19 pandemic, a growing number of states, counties and cities in the United States have issued mandatory stay-at-home orders as part of their efforts to slow down the spread of the virus. We argue that the consequences of this one-size-fits-all order will be differentially distributed among economic groups. In this paper, we examine social distance behavior changes for lower income populations. We conduct a comparative analysis of responses between lower-income and upper-income groups and assess their relative exposure to COVID-19 risks. Using a difference-in-difference-in-differences analysis of 3,140 counties between January 1 and April 15, 2020, we find evidence that stay-at-home orders led to overall improved social distancing. Additionally, we find social distance policy effects on the lower-income group is smaller than that of the upper-income group, by as much as 46% to 54%. We also examined the relationship between personal income, work-related trips, and essential businesses, as defined by the stay-at-home orders. We find that the stay-at-home orders do not reduce low income work trips statistically significantly. That is, a large share of workers in the essential businesses defined by the stay-at-home orders draw from lower-income populations.

1. Introduction

The novel coronavirus, COVID-19, was first detected in the United States on January 20, 2020. Just over three months later, on April 27, more than 1,000,000 people had been affected. Around mid-March, a growing number of states and counties, and cities began to issue mandatory stay-at-home orders (or shelter-in-place orders) as part of their efforts to prevent the spread of the virus. As one of the mitigation measures in response to COVID-19, the stay-at-home orders aim to encourage social distancing behavior in the hope of slowing down the spread of the pandemic. By April 15, 2020, 43 states have implemented statewide stay-at-home orders. Stay-at-home orders

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are intended to reduce the effective reproduction number (R), consequently reducing the rate of pandemic transmission (Anderson et al., 2020; Chen et al., 2020; Painter and Qiu, 2020; Prem et al., 2020). Although social distancing is taking many forms across the country, the fundamental aim is creating distance among individuals.

Many of the current research papers focus on the conceptual and theoretical question of whether social distancing can “flatten the curve”. From these, we know that community members can be quickly reconnected; if each person in the community visits just one person, 90% of households in their community can be reached out by that individual (Goodreau et al., 2020). Meanwhile, social distancing measure has flatten the curve by reducing transmission in the regional studies, such as Hong Kong (Cowling et al., 2020), New York (Harris, 2020), and Washington State (Nelson, 2020), or general studies (Fong et al., 2020). The evidence of the efficacy of social distancing is mixed. Greenstone and Nigam (2020) suggest that even moderate social distancing started early enough has the potential to save many lives, while other studies suggest that severe social distancing measures over a significant duration, particularly in the US (Kissler et al., 2020), are necessary to avoid significant public health consequences (Atkeson, 2020). Despite the success of social distancing in China and other countries (Fang et al., 2020; Prem et al., 2020) in containing the virus spread (Anderson et al., 2020; Painter and Qiu, 2020), encouraging individual responsibility is considered a more viable path to increasing social distancing behavior and slowing down the pandemic in the US (Anderson et al. 2020).

While individual responsibility may play a (potentially) role in the effectiveness of the social distancing as a transmission barrier, it is also likely that other factors interact with individual responsibility to form the complex landscape of adherence. Individuals in the US have reacted to stay-at-home orders in very different ways. These different responses might derive from underlying beliefs regarding COVID-19 and efficacy of social distancing (Allcott et al., 2020), from political ideologies (Allcott et al., 2020; Painter and Qiu, 2020) or from sheer need.

Prior experience with pandemics have had clear disparate effects on socially vulnerable communities, with strong correlations between indicators such the Social Vulnerability Index (SVI) and the number of confirmed cases and fatalities (Nayak et al., 2020). It is quite plausible that extended periods of stay-at-home orders and severe social distancing measures will have deeper adverse effects on socially and economically vulnerable people, especially when combined the structural inequities that produce weak social protection systems. Health insurance, unemployment benefits, paid parental leave, and guaranteed minimum incomes, all reveal many shortcomings in times of this, and other crises (Chapman, 2020; Smeeding, 2005). One extreme example is compelling people (without paid sick leave) to work even they are sick (Miller et al., 2020).

Our research is aimed at contributing to the broader literature on wealth disparities. We use a comprehensive national human mobility dataset covering 3,140 counties and collected between January 1 to April 15, 2020 (Maryland Transportation Institute, 2020). We examine the following research questions: Do lower-income and upper-income groups show differences in their respective responses to the stay-at-home orders under COVID-19? If so, what are the factors driving these differences? We adopt the methods of difference-in-difference-in-differences (DDD) and partially linear varying coefficient model to study the effects of the stay-at-home orders on social distancing and to explore the differences in these effects—if any—between lower-income and upper-income groups.

We begin by describing the methodological approaches and data used to conduct our exploratory analysis. We then turn in section 3 to the results of our baseline estimation using a variety of specifications. Section 4 addresses possible concerns about selection bias and in section 5, we explore the mechanism driving the diverse treatment effects from the stay-at-home orders between the lower-income and upper-income groups. We present the discussion and policy implications in section 6, followed by a brief conclusion.

2. Data and empirical strategy

2.1. University of Maryland COVID-19 Impact Analysis Platform human mobility data

Our study is conducted using a comprehensive national human mobility dataset from the University of Maryland COVID-19 Impact Analysis Platform (Zhang et al., 2020). Data for our primary analysis covers 3,140 counties of the US from January 1, 2020 to April 15, 2020. We conduct all the regressions and tests at the county level. The University of Maryland COVID-19 Impact Analysis Platform provides seven kinds of county-level metrics: social distancing index, the percentage of people staying at home, the number of trips per person, the percentage of out-of-county trips per person, the number of miles traveled per person, the number of work trips per person, and the number of non-work trips per person.[1] The MTI social distancing index ranges from 0 to 100. A larger social distancing index means a higher level of social distancing (Pan et al., 2020). We employ three other dashboard metrics, which are all computed according to standard transportation practices: 1) the "staying at home" which is defined as no trips more than one mile away from home; 2) 'work trips,' defined as going to or coming from a work destination, and 3) 'non-work trips' which are defined in the standard way as trips going to or coming home from non-work location (e.g., park, grocery, restaurant, etc.).[2]

2.2. Supporting data

We also obtained the daily weather data from the National Oceanic and Atmospheric Administration (NOAA), demographic data at the state level and the county level from the American Community Survey of the United States Census Bureau, and labor-related data from the Department of Labor. The number of daily COVID-19 new cases at the county level is obtained from the Johns Hopkins University Github repository.[3] See the descriptive statistics of the data in **Appendix A**.

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[1] For methodologies of computation of these seven metrics, please refer to the section of "DATA AND METRICS SUMMARY" from the University of Maryland COVID-19 Impact Analysis Platform at https://data.covid.umd.edu/about/index.html.

[2] The description of these indicators is defined by the Maryland Transportation Institute (Maryland Transportation Institute, 2020).

[3] The Johns Hopkins University Github repository (https://github.com/CSSEGISandData/COVID-19).

2.3. Exploratory data analysis

Figure 1 plots the evolution of average social distancing index of the upper-income group and the lower-income group from 01/01/2020 to 04/15/2020 in the US. The upper-income group is defined as the counties where the personal income per capita in 2017 was above the average of the state to which they belong. While the lower-income group is defined as the counties where the personal income per capita was below the state average in 2017.[4] We plot the two curves of social distancing index by computing the daily average for each group respectively.

Figure 1 shows the divergence of social distancing patterns between lower-income and the upper-income groups after stay-at-home orders were mandated. Prior to the outbreak, there is no distinct difference in the social distancing index between the lower-income and the upper-income groups. As states began implementing a stay-at-home order, the social distancing indices for both groups increased rapidly. The upper-income group achieved and has largely maintained a higher social distancing level. The major difference between the two groups occurs during weekday periods. We argue that lower-income group are more likely to have to leave home for work.

See the **Appendix I** for the evolution of the social distancing indices of the 50 states plus the District of Columbia.

[4] See the distribution of relative personal income of counties in the US in **Appendix D**. The gap between rich and poor in counties is very large in the US according the data of person income per capita obtained from the United States Census Bureau.

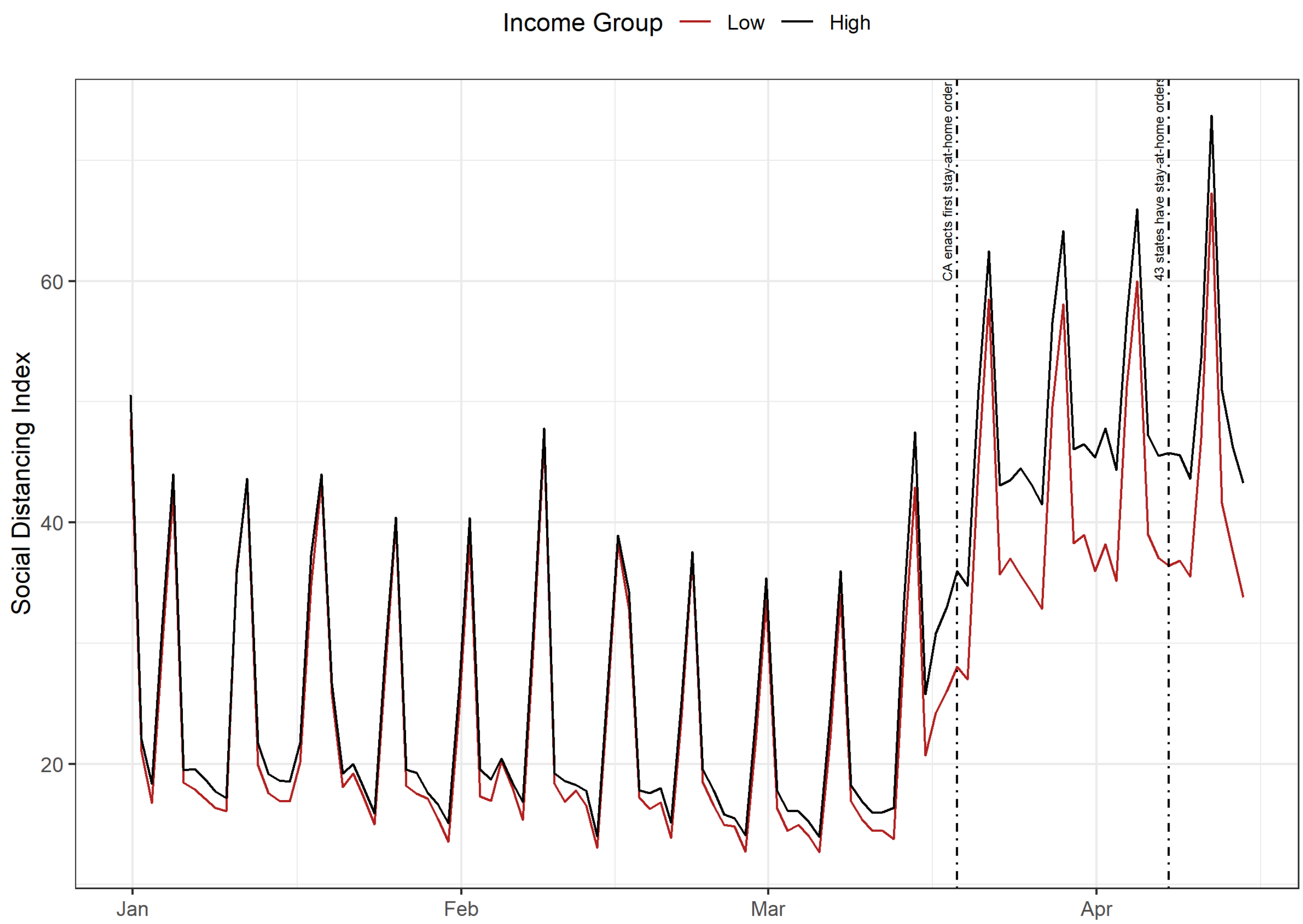

*Figure 1. **Social Distancing Index and COVID-19 Prevalence.** Social distancing patterns begin diverging between the lower-income and upper-income groups after states start enacting stay-at-home orders. The major difference between the two groups occurs during weekday periods.*

2.4. Methodology: difference in difference in differences (DDD)

There are two common challenges to computing the average treatment effects of the stay-at-home orders: selection bias and omitted variable bias. Observational data at the individual level (in this case, an individual's location) only provides a measure of social distancing given the mandates in place. In other words, we do not know how individuals would have acted if the mandates (i.e., treatment) had not been in place. This can potentially lead to a selection bias. Consider the context of the social distancing: if both the control and treatment group had not received the stay at home order, an individual's social distancing index in the treatment group may be different from the social distancing index of a comparable person in the control group. The second major concern is that the assignment to the treatment group may be correlated with unobservable variables which also influence the outcome of interest (Imbens, 2004; Angrist and Pischke, 2008; Abbott and Klaiber, 2011), resulting in an endogenous treatment effect. In the context of the COVID-19 pandemic, there are three types of confounding factors that may lead our estimation to be biased. First, the "festival" effect. The issued dates of the stay-at-home orders are close to two major holidays (Easter and Saint Patrick's Day), when people are more likely to gather. The two holidays are thus correlated with the treatment variable (the variable of stay-at-home orders) and also correlated with residents' social distancing behaviors, which leads the treatment variable to be endogenous. Second, the "panic" effect. People may increase their social distancing level due to panic over COVID-19 as the confirmed COVID-19 cases increase rapidly, and especially after the declaration of states of emergency. Thus, the rapid growth of COVID-19 cases can be correlated with people's social distancing behaviors and also correlated with the implementation of the stay-at-home orders. Third, the timing of adopting the order. States that issued the orders might be different from states that issued the order later or that issued no such order, and such differences could impact social distancing.

To address the first two concerns, we utilize the DDD method to estimate the effects of the stay at home mandate on lower-income group's social distancing index relative to upper-income group. The DDD approach obtains the relative treatment effect through the following equation:

$$\begin{aligned}\beta = \{(E[Y_{istw}|s = treated, t = post, w = low] - E[Y_{istw}|s = treated, t = pre, w = low])\\ -(E[Y_{istw}|s = control, t = post, w = low] - E[Y_{istw}|s = control, t = pre, w = low])\}\\ -\{(E[Y_{istw}|s = treated, t = post, w = high] - E[Y_{istw}|s = treated, t = pre, w = high])\\ -(E[Y_{istw}|s = control, t = post, w = high] - E[Y_{istw}|s = control, t = pre, w = high])\}\end{aligned}$$

where β is the relative treatment effect; Y_{istw} is the outcome of unit *i* in the location *s* and group *w* at time *t*; *post* means the time after receiving the treatment, and *pre* means the time before the treatment; *treated* means the states/counties issued stay-at-home orders, and *control* means the states/counties did not issue the orders; *low* means the lower-income group, and *high* means upper-income group. The DDD approach can rule out the influences of neighborhood and community, natural environment fixed features, and any other unobservable time-invariant factors. More importantly, it can address the concerns about the "festival" effect and the "panic" effect.

In terms of the concern about the timing of adopting orders, it is known that the rapid increase in the number of COVID-19 cases is what drives states to adopt the stay-at-home orders (Sears et al., 2020) . Thus, we control for COVID-19 daily new cases and accumulative cases in our models.

By April 15, 2020, only eight states had not issued any stay-at-home orders. Using the eight states as a control group could be problematic, because the small number of states cannot be fully comparable to all the other states. Fortunately, there is an alternative. The forty-two states in the US that issued stay-at-home orders did so largely on different dates (See **Appendix E** for the different issued dates of statewide stay-at-home orders). Thus, we are able to choose three different time windows (January 1, 2020-March 31, 2020; January 1, 2020-April 3, 2020; January 1, 2020-April 15, 2020) to generate three different control groups with enough states in the control groups. **Figure 2** plots the distribution of the control groups in different time windows. Although the time window 1 may have the most comparable control group, the observations in time window 1 are fewer than in the other two time windows.

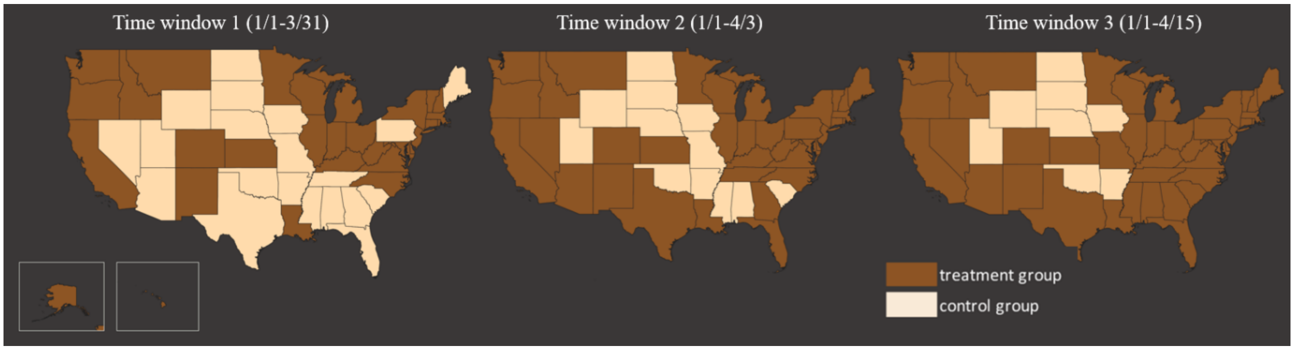

Figure 2. The control groups in three different time windows *(January 1, 2020-March 31, 2020; January 1, 2020-April 3, 2020; January 1, 2020-April 15, 2020). The control groups are defined as the regions without the stay-at-home orders.*

The DDD approach is based on comparison between regions with and without the stay-at-home orders, where the social distancing index in regions without the stay-at-home orders provide a counterfactual for what would have occurred in with stay at home regions the orders not been issued. Whether or not this counterfactual is reasonable depends on whether the groups (with and without social distancing mandates) are *ex ante* similar, in terms of both unobservable and observable features (Davis and Wolfram, 2012). To check this assumption, we adopted the standardized differences (SD) technique, which is the standardized difference of means, to examine differences between variables for the treatment and control groups (Lunt, 2014). We do this for each of the three time periods (See **Appendix B**). We find that time window 1 is the most balanced among the three time windows based on observed socio-economic indicators.

In addition, the parallel trend assumption must also be met between the treatment group and the control group to control for the influence of time-variant factors, including the "festival" effect and the "panic" effect. Both graphical and statistical evidence show that there are no differential trends in the pre-treatment period between the control and treatment groups in any of the time windows (See **Appendix C**).

3. Baseline estimation results

Our DDD approach is described by the following regression model:

$$Y_{it} = \gamma + \beta D_{it} + \alpha D_{it} \cdot I_i + \delta V_{it} + \varphi_i + \vartheta_t + \mu_t + \varepsilon_{it}$$

where Y_{it} is the social distancing index at time t in county i. D_{it} is the treatment variable, which takes value one when county i is under a stay-at-home order at time t. In our regression model, D_{it} takes value one only if county i is in the treatment group and in the post-treatment period; I_i is a lower-income indicator variable, which takes value one if county i's personal income per capita is less than the average personal income per capita of the state to which it belongs. V_{it} is a vector of time-variant control variables, including the number of daily COVID-19 new cases, the number of cumulative COVID-19 cases, daily maximum temperature, daily precipitation, and daily snow at the county level, which could influence the local daily human mobility level. φ_i controls for individual county fixed effects capturing all the time-invariant individual county-specific characteristics. ϑ_t is week-of-sample fixed effects, which captures unobservable common features in each week within the observed time period. μ_t is day-of-week fixed effects, which absorbs variation over the weekly cycle. ε_{it} is an idiosyncratic error term. We cluster our standard errors at the county level, allowing for arbitrary correlations between any two observations within the same county.

The coefficients for the variable of stay-at-home orders in column (1) in **Table 1-3** are difference-in-differences (DID) estimators, which measure the average treatment effect of the stay-at-home orders on the social distancing index of both the lower-income and upper-income groups. This variable indicates that stay-at-home orders increase the social distancing index by 7 to 8 points, on average. The policy effect is economically significant, given that the mean of the outcome variable (the social distancing index) is about 25 to 28 points. That is, the coefficient is large enough in magnitude to be of consideration. However, even after the implementation of the stay-at-home orders, the social distancing index remains low (Ghader et al., 2020), given that the index ranges from 0 to 100.

The coefficients of the interaction terms between the stay-at-home order variable and the lower-income variable in column (2) in **Table 1-3** are DDD estimators, which measure the effect of the stay-at-home orders on the lower-income group's social distancing index relative to the upper-income group. The coefficients are all statistically significant and negative, which implies that the effect of the stay-at-home order on the lower-income group's social distancing index is smaller than the effect on upper-income group by 6-7 points. This suggest that the lower-income group is less likely to follow the stay at home mandate when controlling for other factors, such as the daily weather, the "festival" effect, the "panic" effect, and the time-fixed features.

Columns (3) to (6) in **Table 1-3** present the results from a set of alternative outcome measures; all of the coefficients are consistent with our social distance outcome. The effect of the stay-at-home orders on the percent stay at home in the lower-income group, the number of trips per person, the percentage of out-of-county trips per person, and the miles traveled per person are all smaller than the effects estimated for the upper-income group. This indicates that the stay-at-home orders have less effect on the lower-income group mobility, irrespective of purpose.

Table 1. The estimation results using DID and DDD approaches in time window (01/01-03/31).

	Social Distancing Index (1)	Social Distancing Index (2)	% staying at home (3)	Trips per person (4)	% Out-of-county trips per person (5)	Miles traveled per person (6)
Stay-at-home Order	8.83***	14.08***	6.78***	-0.34***	-2.19***	-4.29***
	(0.26)	(0.58)	(0.33)	(0.02)	(0.20)	(0.35)
Stay-at-home Order × Lower-Income		-6.42***	-3.69***	0.13***	1.00***	1.36***
		(0.62)	(0.34)	(0.02)	(0.21)	(0.38)
Control variables:						
COVID-19 new cases	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 total cases	Yes	Yes	Yes	Yes	Yes	Yes
Max. temperature	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes
Snow	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	262,595	262,595	262,595	262,595	262,595	262,595
R-square	0.64	0.64	0.36	0.36	0.01	0.14
Mean of outcome variable	25.38	25.38	20.65	3.33	34.19	43.52

*Note: Standard errors are clustered at the county level, which are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. The estimation results using DID and DDD approaches in time window (01/01-04/03)

	Social Distancing Index	Social Distancing Index	% staying at home	Trips per person	% Out-of-county trips per person	Miles traveled per person
	(1)	(2)	(3)	(4)	(5)	(6)
Stay-at-home Order	8.13***	13.61***	6.27***	-0.33***	-2.00***	-4.60***
	(0.24)	(0.55)	(0.30)	(0.02)	(0.18)	(0.33)
Stay-at-home Order × Lower-Income		-6.72***	-3.57***	0.14***	0.88***	1.86***
		(0.57)	(0.31)	(0.02)	(0.19)	(0.35)
Control variables:						
COVID-19 new cases	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 total cases	Yes	Yes	Yes	Yes	Yes	Yes
Max. temperature	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes
Snow	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	271,250	271,250	271,250	271,250	271,250	271,250
R-square	0.63	0.64	0.37	0.36	0.01	0.15
Mean of outcome variable	25.79	25.79	20.82	3.32	34.13	43.19

*Note: Standard errors are clustered at the county level, which are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. The estimation results using DID and DDD approaches in time window (01/01-04/15)

	Social Distancing Index	Social Distancing Index	% staying at home	Trips per person	% Out-of-county trips per person	Miles traveled per person
	(1)	(2)	(3)	(4)	(5)	(6)
Stay-at-home Order	7.23***	12.92***	5.86***	-0.31***	-2.16***	-4.03***
	(0.22)	(0.48)	(0.26)	(0.01)	(0.16)	(0.30)
Stay-at-home Order × Lower-Income		-6.95***	-3.68***	0.16***	1.01***	2.25***
		(0.49)	(0.27)	(0.01)	(0.16)	(0.29)
Control variables:						
COVID-19 new cases	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 total cases	Yes	Yes	Yes	Yes	Yes	Yes
Max. temperature	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes
Snow	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	305,870	305,870	305,870	305,870	305,870	305,870
R-square	0.67	0.68	0.41	0.39	0.02	0.21
Mean of outcome variable	27.97	27.97	21.66	3.27	33.83	41.67

*Note: Standard errors are clustered at the county level, which are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4. Accounting for potential selection bias

Here, we consider two possible concerns about selection bias. First, the states of New York, Washington, and California were the earliest states recording a serious outbreak of the COVID-19 pandemic. The patterns behavioral responses in these three states may be different from the other states because, as dissemination occurred, individuals may have been more likely to limit mobility before formal mandates were issued. To address this selection concern, we excluded New York, Washington, and California from the sample and re-ran the models, again using the social distancing index as the outcome variable. The estimated results shown in **Table 4** are consistent with our baseline estimations both in statistical significance and magnitude.

Second, the population density varies significantly across different counties in the US. It can be harder for densely-populated counties to practice social distancing. Thus, the patterns of the residents' response to the COVID-19 in these counties may be different from the other counties. To address this concern, we exclude the densely-populated counties (top 10% of counties in population density; see the distribution of the densely-populated counties in **Appendix F**) from our sample and re-run our models using the social distancing index as the outcome variable. The estimated results shown in **Table 4** are also consistent with our baseline estimations. However, the magnitude of the coefficients is much smaller than the baseline estimations, which implies that stay-at-home orders exert a smaller effect on social distancing in less-populated regions and the difference between the effects on lower-income group and upper-income group is also smaller in these regions.

Table 4. Estimation results addressing the possible concerns about the selection bias

	Time window (1/1-3/31)		Time window (1/1-4/3)		Time window (1/1-4/15)	
	Excluding CA NY WA	Excluding densely populated counties	Excluding CA NY WA	Excluding densely populated counties	Excluding CA NY WA	Excluding densely populated counties
	(1)	(2)	(3)	(4)	(5)	(6)
Stay-at-home Order	12.16***	10.17***	12.16***	9.86***	11.83***	9.32***
	(0.60)	(0.68)	(0.54)	(0.61)	(0.46)	(0.51)
Stay-at-home Order × Lower-Income	-5.00***	-2.57***	-5.81***	-3.15***	-6.38***	-3.86***
	(0.63)	(0.71)	(0.56)	(0.63)	(0.46)	(0.51)
Control variables:						
COVID-19 new cases	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 total cases	Yes	Yes	Yes	Yes	Yes	Yes
Max. temperature	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes
Snow	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	248,126	235,417	256,304	243,178	289,016	274,222
R-square	0.63	0.63	0.63	0.62	0.68	0.67
Mean of outcome variable	25.21	25.05	25.61	25.41	27.77	27.45

*Note: Standard errors are clustered at the county level, which are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5. Mechanism analysis

To explore the mechanism behind the disparate effects of stay-at-home orders on the lower-income and upper-income groups' social distancing behavior, we adopt two alternative outcome variables (work trips per person and non-work trips per person) for our model specification. We look specifically at the relationship between the effects of stay-at-home orders on these outcomes and personal income per capita. Since we do not know the true functional forms between the effect of the stay-at-home orders and other factors, we utilize a flexible semi-parametric method—the partially linear varying coefficient fixed effects panel data model (An et al., 2016; Zhang and Zhou, 2018). The model we adopt allows for linearity in some of the regressors and nonlinearity in other regressors, where the effects of these independent covariates on the outcome variable vary nonparametrically on low-dimensional variables (Cai et al., 2017). The model has the advantage of estimating non-linear heterogeneous effects, and has been widely used (Su et al., 2013; Cai et al., 2017; Delgado et al., 2014; Lundberg et al., 2017; Zhang and Zhou, 2018; Feng et al., 2017),

$$Y_{it} = D_{it} \cdot g(U_{it}) + \beta V_{it} + \varphi_i + \vartheta_t + \mu_t + \varepsilon_{it}$$

where Y_{it} is the outcome variable of county i at time *t*; U_{it} is a continuous variable of an influencing factor associated with the county *i* at time *t*; D_{it} is a treatment variable with functional coefficient $g(U_{it})$; V_{it} is a vector of control variables to control for other time-variant factors, which are the number of daily COVID-19 new cases, the number of accumulative COVID-19 cases, daily maximum temperature, daily precipitation, and daily snow at the county level; φ_i is individual county fixed effects; ϑ_t is week-of-sample fixed effects; μ_t is day-of-week fixed effects. We follow the method developed by An et al. (2016) and Zhang and Zhou (2018) using a linear combination of sieve basis functions to approximate the unknown functional coefficient $g(U_{it})$.

Figure 3 shows the estimated policy effects of stay-at-home orders on social distancing index, work trips per person, and non-work trips per person by the level of personal per capita income. The estimations are consistent across the different time windows. In counties with very low personal income level (<$20k), the effect of a stay-at-home order is significantly negative in time windows 2 and 3 suggesting that stay-at-home orders in these windows reduce very low income (<$20k) level of social distancing. In time window 1, the effects of social distancing on the mobility patterns of the very low income group are unclear.

In term of work-related trips, we find that the stay-at-home orders do not significantly reduce work-related trips for the very low-income group (personal income per capita < $30K). In fact, the results suggest that the stay at home mandates significantly increase the work-related trips in time window 3. The effects of the stay at home policy significantly drive middle income work trips down; the effects of the policy on the higher income group is less clear.

In terms of non-work-related trips, we find that the stay-at-home orders significantly reduce non-work trips for both the middle-income and high-income group statistically in all time windows. However, the orders do not reduce the non-work trips of very low-income people (personal income per capita < $20K) in time windows 2 and 3.

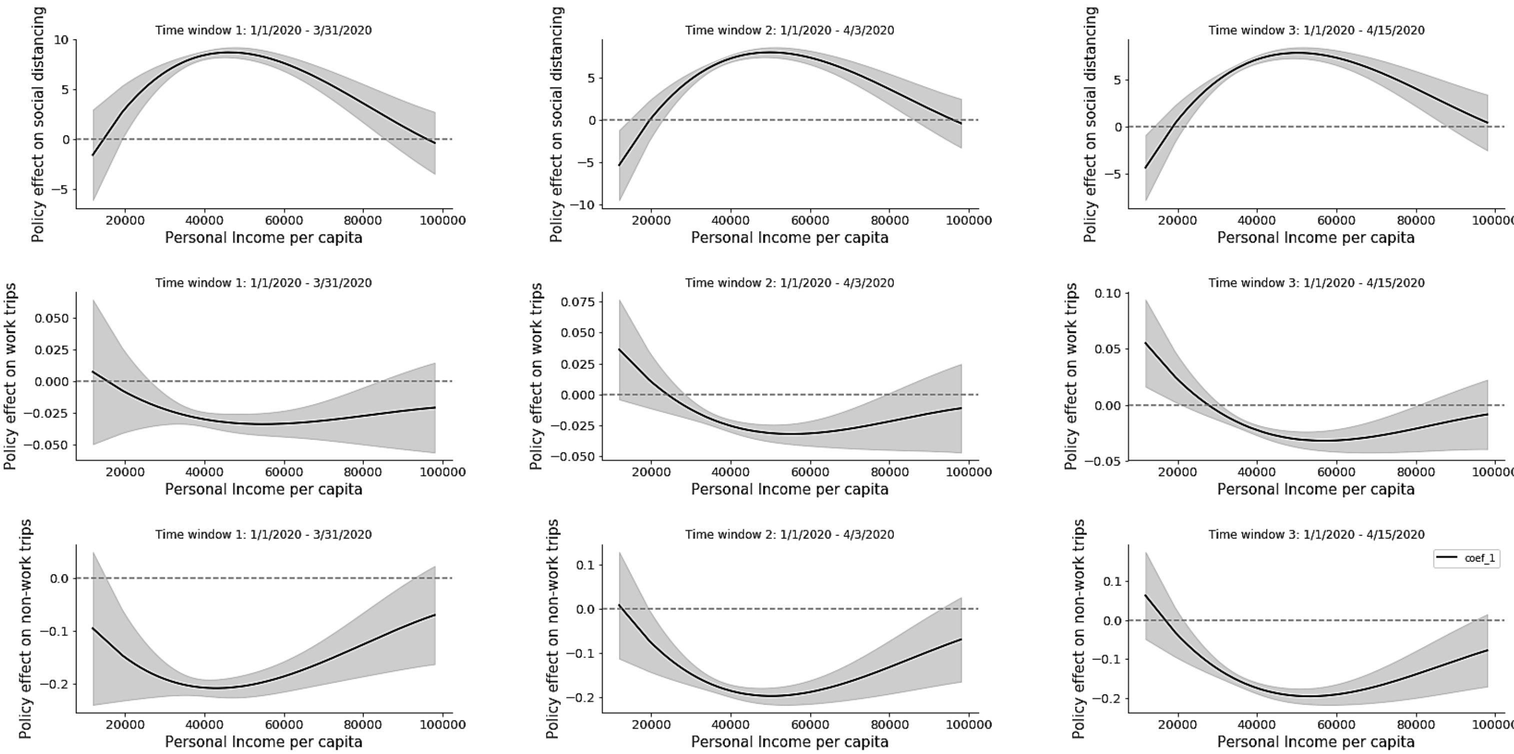

Figure 3. The effect of the stay-at-home orders across income. *The shaded gray area represents 95% confidence intervals.*

To understand the results of this analysis, consider first, that under the stay-at-home orders, "essential" businesses remain open; most essential businesses include medical facilities, grocery stores, auto repair shops, cleaners, restaurants that offer take-out and delivery, and many delivery/transport options in the transportation sector (See **Appendix G**). Within the essential businesses, all sectors except the medical and financial sectors have relatively low wages (**Table 5**). The workers with lower-wages account for about 76% of all employment in essential businesses. During the COVID-19 pandemic, the demand for some of the essential businesses has greatly increased (Tomer and Kane, 2020).

Second, the stay-at-home orders are likely to be associated with at least some non-essential business closures. This is particularly true for certain types of businesses such as restaurants, bars, malls, fitness centers, theaters, etc., where most of the employees are part-time or paid hourly, or where business models do not allow employees to work from home. Thus, the stay-at-home orders in essence "force" these workers to unemployment. When we look at the correlation between the unemployment claims and occupation, we find that states with a higher share of service occupations are more likely to have higher unemployment insurance post-COVID-19 outbreak (see detailed results in **Appendix H)**. Most of the unemployed also receive relatively low wages.

Table 5. The hourly rate and employment number of essential businesses in stay-at-home orders

Essential business	Hourly rate	Employment per 1,000 jobs	Employment % of the essential business
Grocery stores, liquor stores, farmer's markets*	$14.10	21	8.59%
Hospitals, medical facilities, and pharmacies	$40.21	59.05	24.17%
Cable, phone, and internet infrastructure and providers	$28.13	1.52	0.62%
Banks and financial institutions	$19.60	19.82	8.11%
Laundromats and dry cleaners	$12.22	1.42	0.58%
Auto repair shops and gas stations	$21.71	5.58	2.28%
Child care facilities (with restrictions)	$12.27	3.82	1.56%
Restaurants that offer take-out, grab and go, and delivery	$12.38	56	22.92%
Transportation and logistics	$16.91	76.13	31.16%
Lower-income groups	**$21.56**	**185.29**	**75.83%**

Data source: May 2019 National Occupational Employment and Wage Estimates, United States Bureau of Labor Statistics.
*this data is from May 2018 National Industry-Specific Occupational Employment and Wage Estimates, Sectors 44 and 45 - Retail Trade.

One obvious concern of this mechanism analysis is that our division of the upper-income group and the lower-income group is based on income aggregated at the county level, while the work activities occur at an individual level. That is, it is highly likely, for example, that there are higher-income households living in lower-income counties. This concern can be mitigated for the following reasons: first, the number of counties in the US is 3,140, which is large enough to reflect differences among counties. Second, within each state, economic inequality is evident among counties as we show in **Appendix D**. The range of relative personal income[5] in each county within a state is from 0.2-1.8, which provides enough observational variation for statistical inference. Third, if the average personal income of a county is below the state average, it indicates that the percentage of low-wage workers is likely to high in the county.

6. Discussion

Our study examines a unique timeframe for the specific governmental policy intervention of stay-at-home orders. Using the dataset from the University of Maryland COVID-19 Impact Analysis Platform, we analyze social distancing behavior changes that resulted from the stay-at-home orders, with a particular interest in assessing how the orders affected different income groups. We find that the stay-at-home orders increased the social distancing index, as defined by the UMD

[5] The relative personal income is defined as the ratio of a county's personal income per capita to the personal income per capita of the state to which it belongs.

dashboard, by 7 to 8 points (with an overall average social distancing index of 28). The effect of the stay-at-home orders on the social distancing index for lower-income groups is smaller than the effect on the upper-income group, which ranges from 6 to7 points, by as much as 46% to 54%.

This suggests that the lower-income group is less likely to (be able) to follow the order to stay at home, controlling for other factors. Additionally, we find that the effects of the stay-at-home orders on the lower-income group's mobility, including the percent of time at home, the number of trips per person, the percentage of out-of-county trips per person, and miles traveled per person are all smaller than the effects on the upper-income group. Importantly, our study shows that the stay-at-home orders do not significantly reduce the work-related trips of the very low-income (personal income per capita < $30K), and the orders can even significantly increase this group's work-related trips, while reducing middle and perhaps high income work trips. In terms of non-work-related trips, we find that the stay-at-home orders reduce non-work trips for middle and high income groups. However, the orders do not reduce non-work trips for the very low-income (personal income per capita < $20K) across most of our study period.

Our empirical results demonstrate that the economic gap, and especially the work structure gap, produces disproportionate effects on the ability of low wage workers to reduce mobility, despite orders to shelter-in-place. The gap in the ability to adhere to stay at home orders is real and statistically significant, even after controlling for a range of key factors which might impact these behavior changes.

Lower social distancing for lower-income groups can be traced to policy challenges in which unintentional discrimination among different groups result (Fiscella and Williams, 2004; Konisky, 2009; Ruben and Pender, 2004; Soroka and Wlezien, 2008). Policymaking decisions also confront trade-offs between interest groups (Gilens, 2005; Link and Phelan, 1995), and policies can be influenced by citizens based on their financial resources (Mechanic, 2002). Some of these challenges lead to policy outcomes which reflect the preferences of the affluent, but not the interests of the lower-income or the lowest income group. Institutional discrimination can also block the effectiveness of the policies.

Institutional discrimination is well discussed in literature. Our findings contribute to the discussion by highlighting fundamental structural factors that cause inequality within the United States. The United States has a high level of economic inequality compared to other OECD nations (Smeeding, 2005). Thus, it is likely that, as the literature suggests, behavioral responses to stay-at-home orders can be traced to the "fundamental causes" related to socioeconomic status and social support, where there exist disproportionate effects of environmental hazards, such as air pollution, waste disposal, etc. between the poor and the rich (Marshall, 2008; Morello-Frosch et al., 2001). Consider transportation where existing transportation policies exacerbate inequities for low-income groups, minority populations, or communities of color by limiting accessibility to key services (Karner and Niemeier, 2013; Lucas, 2012; Pereira et al., 2017; Sanchez et al., 2003). The absence of, for example, health care services, grocery stores, job opportunities, etc., amplify the negative consequences of wealth disparity (Dorn et al., 2020; Sanchez et al., 2003; Sanchez and Wolf, 2005).

Structural factors almost certainly contribute to the disproportionate impact on the vulnerable groups under the current framing of stay-at-home orders. These factors further prevent vulnerable groups from actually practicing social distancing. Notably, governments have specifically outlined that "essential" businesses remain open even while stay-at-home orders are in place. The definition of "essential businesses" varies in scope and coverage among states, but generally highlights survival needs, both physical and mental. Although the current literature is mixed (Abouk and Heydari, 2020; Adams-Prassl et al., 2020), one consequence of "essential" businesses remaining open is that this may have the effect of "forcing" some workers to work when they would prefer to social distance, or working longer or irregular hours than usual (Cove and Gupta, 2020). Goodreau has shown that any community that includes residents with essential jobs will generates social connections (Goodreau et al., 2020) between people. A large portion of these essential-job workers are likely to belong to low-income groups (Dorn et al., 2020), and unless we wish to move them to an island, we are all affected by the burdens we place on vulnerable communities.

There are ways we can reduce the negative effects on vulnerable communities during COVID. One possible mitigation measure is prioritizing financial, health care and economic support for the vulnerable groups, especially for essential workers. At the time of our writing, it had been over 45 days since the first stay-at-home order was initiated in the Washington State. However, no bills have been passed to prioritize the health or safety of these workers. Current proposed bills, such as Patriot Pay (aiming to give a raise to essential works) and Opportunities for Heroes Act (aiming to provide education-related assistant), are still under discussion. Even if they are passed eventually, their limited coverage and delaying implementation can only partially remediate the losses that these workers experienced.

Another possible mitigation measure is providing additional services for unemployed low-income populations. COVID-19 is hitting these individuals harder than others. By the end of the week May 02, there were 22 million jobless Americans, a record high unemployment rate of 15.1 (U.S. Department of Labor, 2020). Unemployment will likely remain elevated even after the COVID-19 runs its course. The newly released IMF special report forecasts a -3 percent contraction in 2020 for the global economy, which is much worse than the financial crisis in 2008 (IMF, 2020). While in the United States, due to the response to the COVID-19 pandemic, the real GDP decreased 4.8 percent in the first quarter of 2020 (BEA, 2020). Others, such as the Congressional Budget Office and Morgan Stanley, also predict a sharp drop in the second quarter. The decline could range from 28 percent to 38 percent (Swagel, 2020). As a result, policy makers, despite supporting the current unemployment insurance with extended benefits, also need to focus on providing re-employment services to low-income groups and ensuring adequate and smooth transition to new jobs.

The third possible mitigation measure is establishing an open and transparent communication channel between the government and the vulnerable groups. Because our paper not only illustrates how inequalities in social distancing and associated behavior changes are pervasive among counties with lower income, it also sheds light on their origins or the reasons for their persistence. In this context, questions can legitimately be raised about whether lower-income groups are less aware of the severity of the disease. If true, it might reflect policies that do not have the capacity or intent of providing enough education and communication channels. For this reason, some have also suggested an increased role for the government in educating and providing timely information to the general public (Chen et al., 2020; Mechanic, 2002).

Findings from our study point to potential areas for future research. First, research can be conducted to analyze the potential relationship between COVID-19-associated hospitalization rates, the infection fatality rate, the growth rate of new cases and personal income. Additionally, further research should examine the disparate impact of stay-at-home orders on indicators among economic groups. Currently, it is still too early to test the effectiveness of stay-at-home orders on these standard indicators. Finally, due to the special characteristics of COVID-19, we should also consider that the early outbreak in the United States has been linked to recent international and domestic travel, and these cases are more likely to have originated in upper-income counties.

7. Conclusion

With the rapid COVID-19 escalation, going out for "essential" work activities and other non-work activities might expose low income populations to a higher health risk. In this unequal distribution of potential risk caused by stay-at-home orders, we find that wealth disparities play an explanatory role even after controlling for a number of key factors, such as daily weather, the "festival" effect, the "panic" effect, and all of the time-fixed features. The lower-income group bears a disproportionate burden of exposures to health risks due to stay-at-home orders and COVID-19. The relevance, however, is not limited to this current severe pandemic phase in the United States, but also links to the broader policy world in terms of vulnerability of the poor in the United States and around the globe.

Our paper suggests the need for innovative policy mechanisms as well as targeted strategies to mitigate the impacts of the wealth disparities. Over the course of the COVID-19 pandemic, we believe that ensuring the life quality of lower-income workers and families is essential to sustainable economic development, even in the post-pandemic world.

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Appendix:

A. The descriptive statistics of the data

Variable	Obs.	Mean	Std. Dev.	Min	Max	Unit
Social distancing index	332,840	27.97	15.5	0	100	-
% staying at home	332,840	21.66	7.65	0	100	%
Trips per person	332,840	3.27	0.56	0	9.4	-
% Out-of-county trips per person	332,840	33.83	11.48	0	100	%
Miles traveled per person	332,840	41.67	15.41	0	297.9	miles
Work trips per person	332,840	0.45	0.23	0	5	-
Non-work trips per person	332,840	2.82	0.47	0	9.1	-
COVID-19 daily new cases	332,840	1.89	46.18	0	7837	-
COVID-19 cumulative cases	332,840	22.17	657.94	0	118302	-
Daily maximum temperature	305,870	51.04	16.01	-34.67	85.07	Fahrenheit
Daily precipitation	305,912	0.12	0.32	0	6.21	inches to hundredths
Snow	305,912	0.11	0.56	0	30.75	inches to tenths
Person income per capita	327,222	41973.64	11565.5	11937	233860	2017$

B. Covariate balance check

The following table compares the major observed characteristics of the treatment groups with the control groups in the three different time windows. We adopted the standardized differences (SD) technique, which is the standardized difference of means, to access the differences between variables of the treatment and control groups (Lunt, 2014). If the absolute value of SD is smaller than 0.1, we can conclude that the covariate is balanced between the treatment and control groups (Lunt, 2014). After we ran the standardized differences test, the results show us that nine out of 14 covariates in time window 1 between the two groups differ by less than 0.1 absolute number of SD. While in time window 2 and 3, we have less covariates differ by less than 0.1 absolute number of SD. As a result, time window 1 has the most balanced groups among the three groups.

Table B. Covariate balancing check between the control group and the treatment group

Indicators	Time window: 1/1-3/31			Time window: 1/1-4/3			Time window: 1/1-4/15		
	Mean in treated	**Mean in Untreated**	**Standardized diff.**	**Mean in treated**	**Mean in Untreated**	**Standardized diff.**	**Mean in treated**	**Mean in Untreated**	**Standardized diff.**
Reg Gas Price 20200419	1.89 (0.40)	1.77 (0.28)	0.34	1.9 (0.38)	1.64 (0.20)	0.85	1.87 (0.38)	1.69 (0.25)	0.55
Population	6335733 (7064760)	6009481 (6925749)	0.05	7490125 (7763612)	3216498 (1912608)	0.75	6879505 (7386678)	2148717 (1312010)	0.9
Sex ratio (males per 100 females)	97.81 (2.96)	97.65 (3.57)	0.05	97.32 (3.00)	98.76 (3.75)	-0.42	97.27 (2.96)	100.69 (3.20)	-1.1
White population in one race %	76.59 (13.46)	76.14 (12.95)	0.03	75.09 (14.17)	79.56 (10.08)	-0.36	75.09 (13.52)	84.58 (6.58)	-0.89
Black population in one race %	9.56 (8.53)	13.8 (13.11)	-0.38	11.13 (10.21)	11.11 (11.60)	0.002	12.17 (10.88)	4.73 (4.79)	0.89
Vote population %	0.73 (0.03)	0.73 (0.38)	0.1	0.73 (0.03)	0.73 (0.03)	-0.03	0.73 (0.03)	0.72 (0.03)	0.23
Per capita income	33957 (4975)	31579 (5977)	0.43	34044 (5662)	29821 (2861)	0.94	32398 (5688)	30120 (2733)	0.52
Labor force (18+) %	63.84 (3.45)	63.35 (4.27)	0.13	63.71 (3.345)	63.5 (4.74)	0.05	63.3 (3.59)	65.85 (4.16)	-0.66
Unemployment rate	4.71 (0.92)	4.69 (1.24)	0.02	3.05 (0.6)	2.62 (0.55)	0.74	3.05 (0.59)	2.33 (0.27)	1.587
Drive to work	77.01 (6.17)	78.37 (10.55)	-0.16	76.05 (8.58)	81.63 (3.02)	-0.87	77.03 (8.46)	80.46 (2.94)	-0.55
Carpooled to work	9.19 (1.23)	9.29 (1.36)	-0.08	9.11 (0.90)	9.51 (1.43)	-0.33	9.18 (1.04)	9.54 (1.34)	-0.3
Private wage and salary workers	79.31 (4.08)	79.23 (3.15)	0.02	79.45 (3.97)	78.71 (2.87)	0.22	79.25 (3.84)	77.85 (2.76)	0.43
Government workers	14.69 (3.62)	14.44 (3.10)	0.07	14.51 (3.65)	14.9 (2.53)	-0.13	14.77 (3.55)	15.50 (2.46)	-0.25
Land area	67639.91 (95106.54)	70870.06 (51030.59)	-0.04	70072.28 (96397.89)	65906.88 (19666.11)	0.06	68284.12 (87470.26)	72173.28 (14394.48)	-0.06

Note: standard deviation in parentheses; Standardized differences (SD) are the standardized difference of means. If the SD is smaller than 0.1, we can conclude that the covariate is balanced between the treatment and control groups (Lunt, 2014).

C. Pre-treated parallel trend

The parallel trend assumption must also be met between the treatment group and the control group to control for the influence of time-variant factors, including the "festival" effect and the "panic" effect. It is impossible to test the parallel trend assumption in the post-treatment period. Thus, we plot the daily average social distancing index of the treatment group and the control group in the pre-treated period to reflect the pre-treated trends between the two groups. **Figure C** shows the pre-treated trends in the three different time windows and provides evidence that the pre-treated trends between the treatment and control groups are generally parallel in all the time windows. Time window 1 has more parallel trends than the other two windows. This implies that the control group in time window 1 is the most comparable one. We can also observe a rapid growth after the outbreak of the COVID-19 (around 03/15/2020). This suggests the panic effect we discussed earlier where people spontaneously increased the social distancing level as the confirmed COVID-19 cases increased rapidly and the state of emergency was declared, but before a formal stay-at-home was ordered. We also do not find statistical evidence of differential trends between the control and treatment groups in any of the time windows using difference-in-means *t*-tests. We fail to reject the null hypothesis that the average change in social distancing index of the treatment group is different from that of the control group in the pre-treatment period (the *t*-statistics of the three time windows are -0.91, -0.82, and -1.13, respectively).

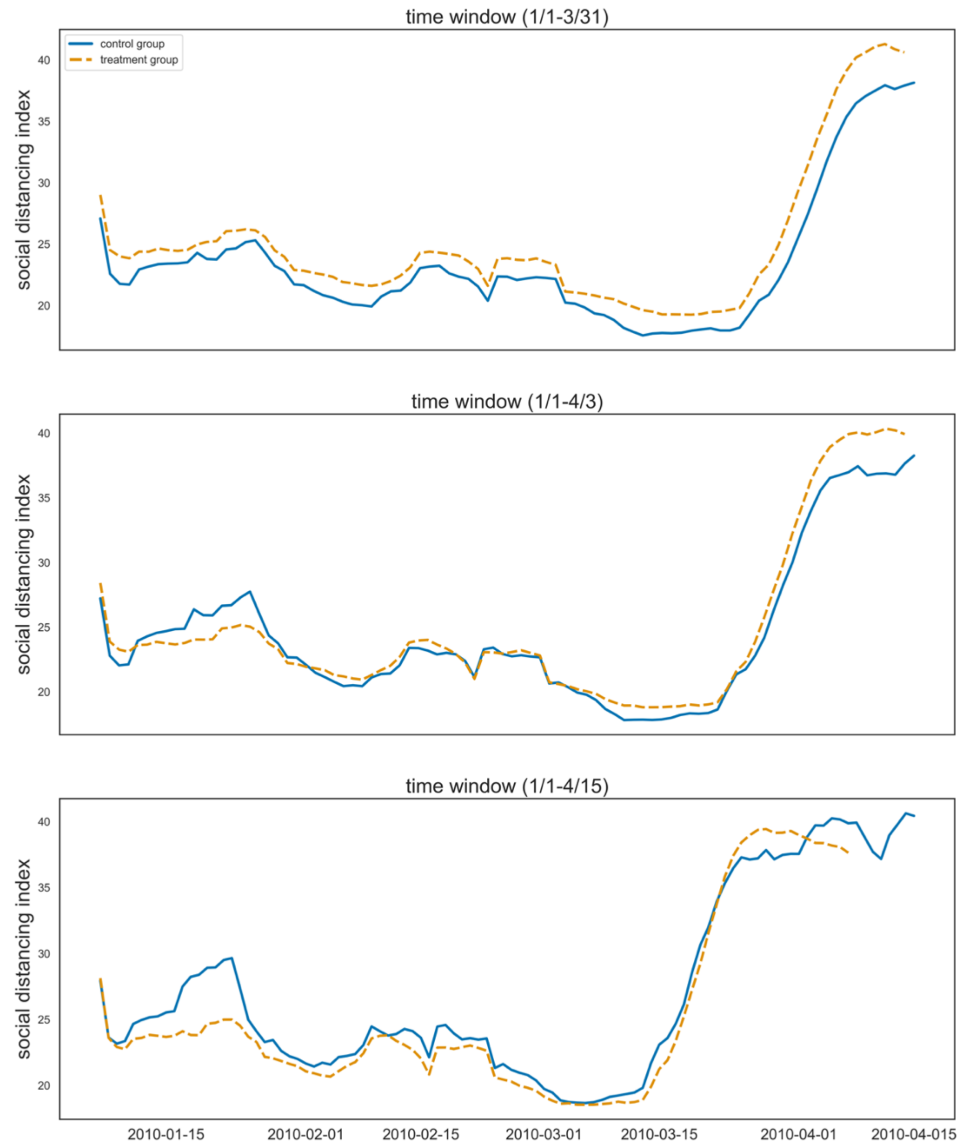

Figure C. The pre-treated trends between the control group and the treatment group. *The pre-treated trends between the treatment and control groups are generally parallel in all time windows, with evidence of a greater number of parallel trends in window 1. Note also a period of rapid growth after the outbreak of the COVID-19 (around 03/15/2020).*

D. The distribution of relative personal income of counties in the United States

We plot the distribution of relative personal income of counties in the United States. The relative personal income is defined as the ratio of a county's personal income per capita to the personal income per capita of the state to which it belongs. Based on the **Figure D**, the gap between rich and poor in counties is very large.

One obvious concern derives from the data's measurement level. Our division of the upper-income and the lower-income group is based on income aggregated at the county level, while the work activities are actually at a personal level. As a result, it is highly likely that there are higher-income residents living in a given lower-income county, and vice-versa. This concern can be addressed with the following argument: first, the number of counties in the United States is 3,140, which is large enough to give a high resolution to reflect the differences among counties. Second, within each state, economic inequality is evident among counties as we show in **Figure D**. The range of relative personal income in each county is from 0.2-1.8. Third, if the average personal income of a county is below the state average, it indicates that the percentage of low-wage workers is high in this county. Fourth, we should also consider that work mobility between counties is quite common in the United States.

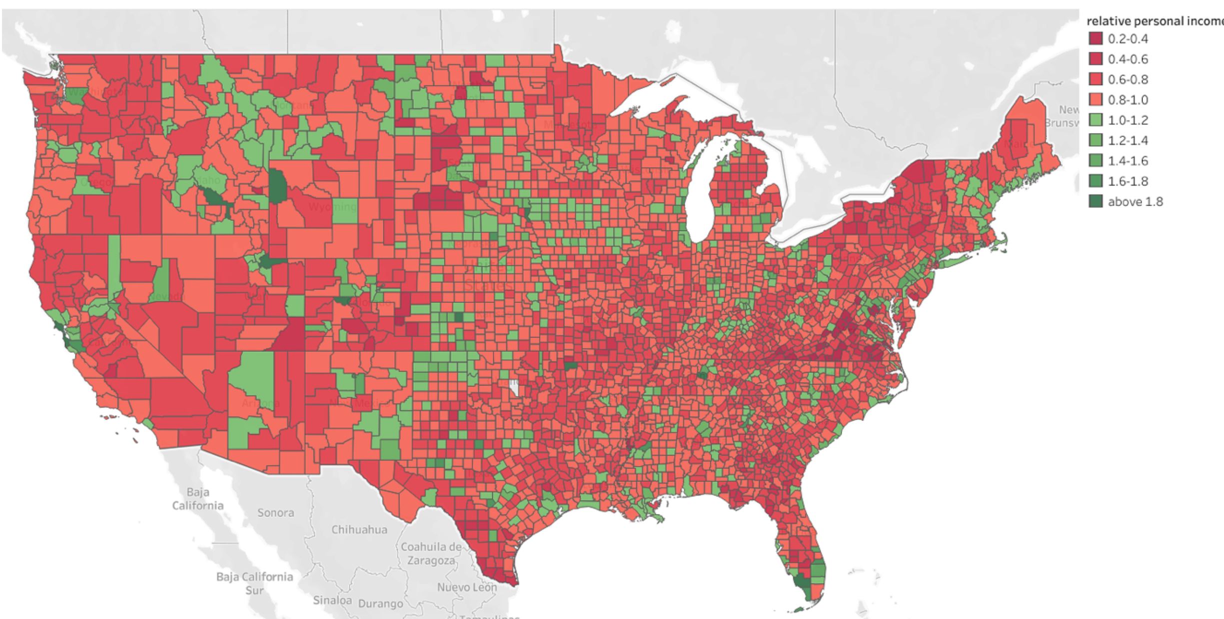

***Figure D**. The distribution of relative personal income of counties in the United States*

E. The issued dates of state-wide stay-at-home orders

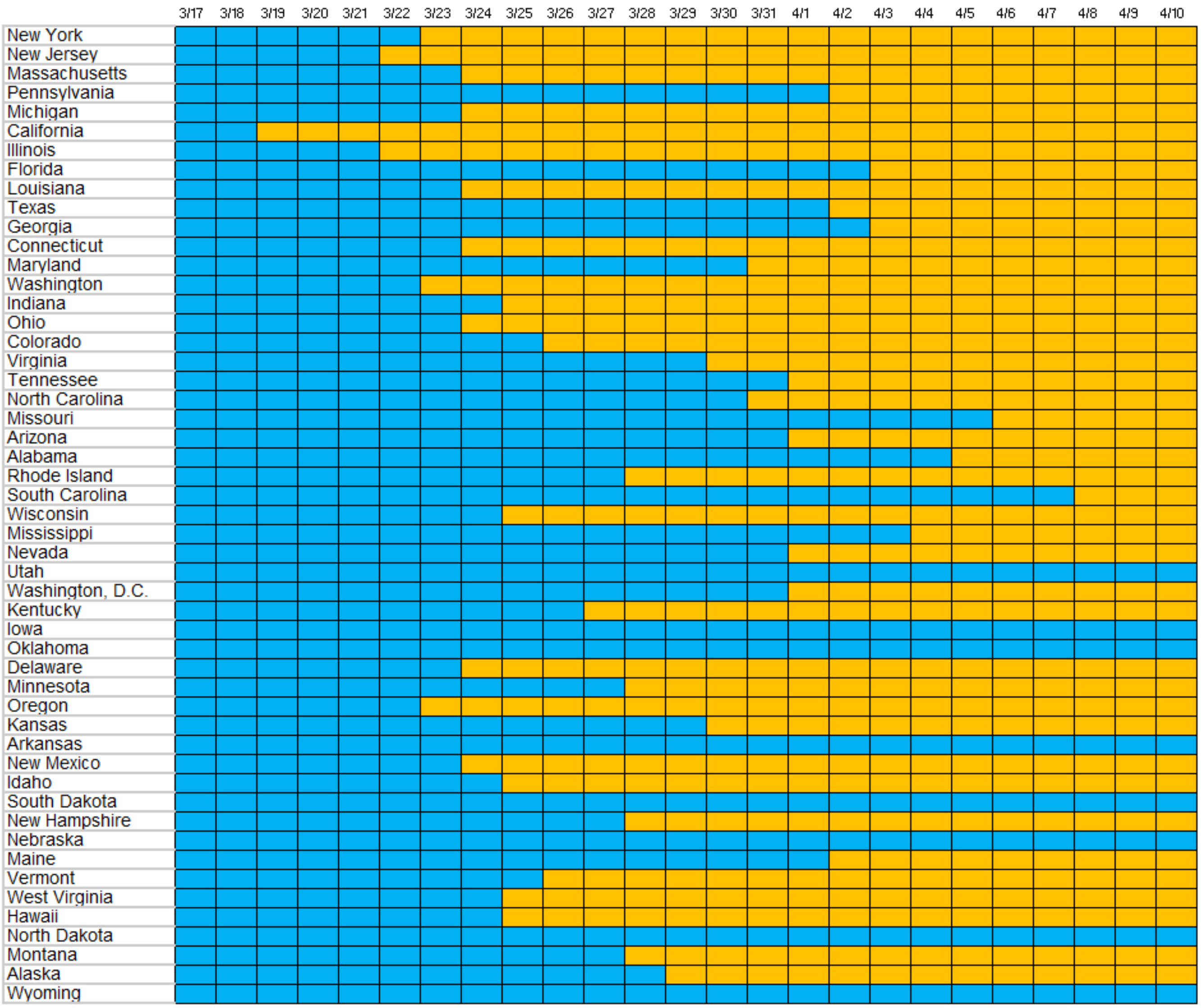

Figure E. *The issued dates of state-wide stay-at-home orders in the United States. Yellow blocks represent the effective dates.*

F. The distribution of highly populated counties

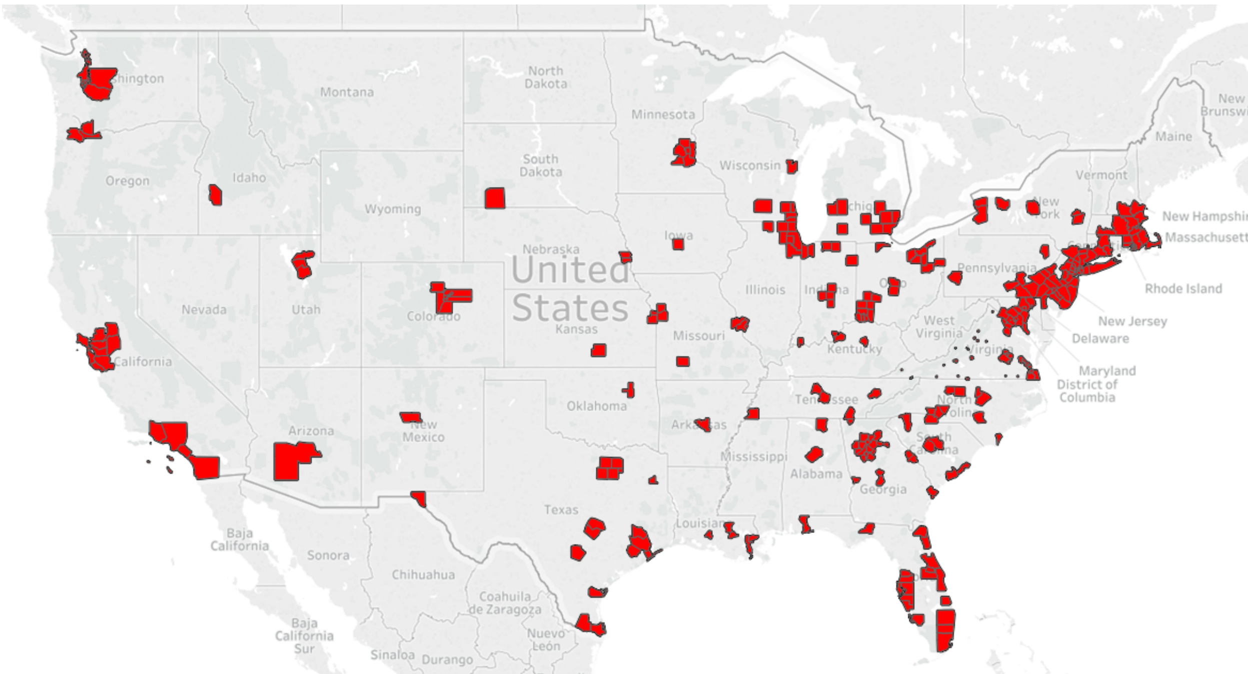

Figure F. *The distribution of highly populated counties (top 10% of counties in population density)*

G. Table of Essential business

Essential business	Sub-category	Hourly rate	Annual rate	Employment	Employment per 1,000 jobs
Grocery stores, liquor stores, farmer's markets	Food and Beverage Stores (4451 and 4452 only)	14.09	$29,300	2,923,390	19.9
	Beer, Wine, and Liquor Stores	14.31	$29,760	159,530	1.09
Hospitals, medical facilities, and pharmacies	Healthcare Practitioners and Technical Occupations	40.21	$83,640	8,673,140	59.051
Cable, phone, and internet infrastructure and providers	Radio and Telecommunications Equipment Installers and Repairers	$28.13	$58,510	222,850	1.517
Banks and financial institutions	Financial Clerks	$19.60	$40,770	2,910,660	19.817
Laundromats and dry cleaners	Laundry and Dry-Cleaning Workers	$12.22	$25,420	209,330	1.425
Auto repair shops and gas stations	Automotive Technicians and Repairers	$21.71	$45,150	818,920	5.576
Childcare facilities (with restrictions)	Childcare Workers	$12.27	$25,510	561,520	3.823
Restaurants that offer take-out, grab and go, and delivery	Food Preparation and Serving Related Occupations*	$12.38	$25,742	8,228,790	56
Transportation and logistics	Passenger Vehicle Drivers	$17.21	$45,830	879,540	$5.99
	Bus Drivers, Transit and Intercity	$22.03	$45,830	179,510	1.222
	Ambulance Drivers and Attendants, Except Emergency Medical Technicians	14.23	$29,600	14,740	0.1
	Driver/Sales Workers and Truck Drivers	$20	$42,170	3,223,840	21.949
	Subway and Streetcar Operators	30.66	$63,770	111,090	0.073
	Laborers and Material Movers	14.7	$30,570	6,168,600	41.999
	Shipping, Receiving, and Inventory Clerk	17.32	$36,030	704,910	4.799

Data source: May 2019 National Occupational Employment and Wage Estimates, United States Bureau of Labor Statistics.
*this data is from May 2018 National Industry-Specific Occupational Employment and Wage Estimates, Sectors 44 and 45 - Retail Trade.

H. The correlations between the unemployment insurance claims and occupations

We obtain the data of the number of unemployment insurance claims at the state level on the three weeks (3/21/2020; 3/28/2020; 4/4/2020) since the outbreak of COVID-19 from the United States Department of Labor. We use the number of unemployment insurance claims per 10,000 persons at the state level as the outcome variable, and the percentage share of different occupations and industries at the state level as the independent variables. The following table presents the OLS estimation results. We find that the share of service occupations has the largest correlation with the number of unemployment insurance claims.

	# Unemployment Insurance Claims/per person (10000)		**# Unemployment Insurance Claims/per person (10000)**
Service	**29.68*** **	Arts, entertainment, and recreation	**11.92** **
	(5.81)		(5.55)
Production, transportation, and materials	**18.26*** **	Agriculture, forestry, fishing	-6.66
	(4.68)		(8.07)
Management, business, science, and arts	**13.81*** **	Construction	-19.85
	(3.40)		(12.61)
Sales and office	-0.87	Manufacturing	-0.02
	(6.23)		(5.5)
		Wholesale, trade	28.69
Obs	153		(22.89)
R-square	0.16	Retail trade	-8.33
			(10.73)
		Transportation, and warehousing	-6.59
			(12.21)
		Information	1.17
			(23.87)
		Finance and insurance, and real estate	-9.38
			(7.54)
		Professional, scientific, and management	-1.82
			(9.66)
		Educational services, and health care	5.46
			(6.37)
		Obs	153
		R-square	0.18

*Note: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data source: United States Department of Labor.

I. The evolution of the social distancing indices of the 50 states plus the District of Columbia

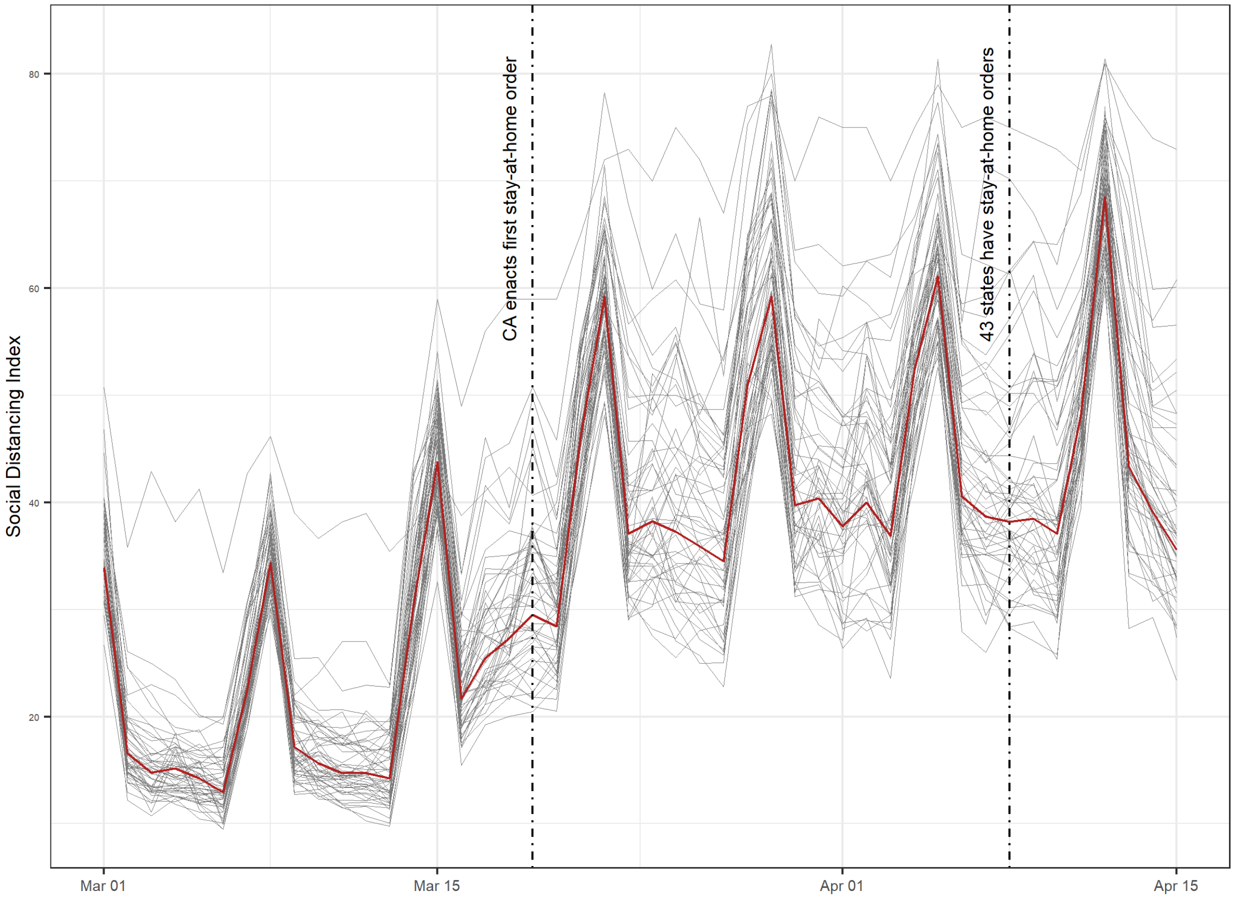

Figure I. *The evolution of the social distancing indices. Gray lines are the social distancing indices of 50 states plus the District of Columbia. The red line is the national average social distancing index.*