Journal of Transport Geography 89 (2020) 102894

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

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

Jiehong Lou [a,1], Xingchi Shen [a,*,1], Deb Niemeier [b]

[a] School of Public Policy, University of Maryland, College Park, MD 20742, USA
[b] Department of Civil and Environmental Engineering, University of Maryland, College Park, MD 20742, USA

ARTICLE INFO

Keywords:
COVID-19
Stay-at-home order
Social distancing
Lower income
Disparate impact
Essential business

ABSTRACT

In response to the COVID-19 pandemic, a growing number of states, counties and cities in the United States 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 3140 counties, we find social distance policy effect on the lower-income group is smaller than that of the upper-income group, by as much as 46% to 54%. Our explorations of the mechanisms behind the disparate effects suggest that for the work-related trips the stay-at-home orders do not significantly reduce low income work trips and this result is statistically significant. That is, the share of essential business defined by stay-at-home orders is significantly negatively correlated with income at county level. In the non-work-related trips, we find that both the lower-income and upper-income groups reduced visits to retail, recreation, grocery, and pharmacy visits after the stay-at-home order, with the upper-income group reducing trips more compared to lower-income group.

1. Introduction

The novel coronavirus, COVID-19, was first detected in the United States on January 20, 2020. Over five months later, more than 3,300,000 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 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

* Corresponding author at: School of Public Policy, University of Maryland, Van Munching Hall, College Park, MD 20742, USA.
E-mail address: xcshen@umd.edu (X. Shen).
[1] Lou, and Shen are co-first-authors.

https://doi.org/10.1016/j.jtrangeo.2020.102894
Received 13 July 2020; Received in revised form 12 October 2020; Accepted 15 October 2020
Available online 30 October 2020
0966-6923/© 2020 Elsevier Ltd. All rights reserved.

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, as evidenced by strong correlations between indicators such the Social Vulnerability Index (SVI) and the number of confirmed cases and fatalities (Nayak et al., 2020). Past pandemics, such as SARS (2003), H1N1 (2009), MERS (2012), Ebola (2014), Zika (2016) help create enduring inequalities (Furceri et al., 2020). It is quite plausible that 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).

The myriad of outcomes to the stay-at-home orders can very likely be traced to socioeconomic status and the lack of social support systems. Take transportation where current research on COVID-19 which finds that different mobility responses between income groups, where wealthier neighbors are able to flee to a safer place, while residents in poor neighborhoods are bound to pandemic epicenters (Andersen, 2020; Coven and Gupta, 2020). The pandemic response exacerbates existing transportation policies which produce restricted accessibility to key services resulting in inequitable effects on low-income groups, minority populations, or communities of color (Karner and Niemeier, 2013; Lucas, 2012; Pereira et al., 2017; Sanchez et al., 2003). In turn, this leads to less social and economic opportunities, including access to health care services, grocery stores, job opportunities, etc., and the negative consequences of wealth disparity becomes a larger social issue (van Dorn et al., 2020; Sanchez et al., 2003; Sanchez and Wolf, 2005). Many original intentions and policies designed to improve public goodwill may have unintended negative effects or aggravate existing structural inequity.

Our research is aimed at contributing to the broader literature on wealth disparities. To study the disparate mobility behaviors, our study uses two comprehensive national human mobility datasets. One dataset is from the University of Maryland COVID-19 Impact Analysis Platform (Zhang et al., 2020), and the other dataset is from the Google Community Mobility Reports. Data for our primary analysis covers 3140 counties of the US from January 1, 2020 to April 15, 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) 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 then conduct a deeper analysis to study the mechanisms that cause the disparate effects between the lower-income and upper-income groups by separating the trips between work and non-worked activities.

Our research evaluates differences in the lower-income and upper-income groups' respective responses to the stay-at-home orders under COVID-19 and deepens current knowledge about the diverse effects that policy levers can have between lower and upper-income groups. That is to say, studying the mechanisms behind the disparate effects is a must, because it not only provides a window of opportunity to bridge the gap between the lower-income and upper-income groups, but also it can reveal new courses of action that help to mitigate inequalities in future disasters.

We begin by describing the methodological approaches and data used to conduct our exploratory analysis in section 2. 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) developed by the Maryland Transportation Institute (MTI). Data for our primary analysis covers 3140 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 six kinds of county-level metrics: social distancing index, the percentage of people staying at home, the number of 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.[2] 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). Three of the six dashboard metrics 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.).[3] The MTI mobility data is representative of the county population, and has been validated by independent datasets such as the American Community Survey and National Household Travel Survey (Zhang et al., 2020; Zhang and Ghader, 2020).

2.2. Supporting data

We also use another source of mobility related data collected from the Google Community Mobility Reports (Google, 2020).[4] The Google Community Mobility Reports provide an aggregated and anonymized global sets of data by Google from users who have turned on the Location History setting. This dataset distributes daily "movement trends over time by geography, across different categories of places such as retail and recreation, groceries and pharmacies, parks, and transit stations" (Google, 2020). To standardize the measures of local movement, the Google mobility data are the percent change compared to the baseline in visits to places mentioned above within each county. The baseline is the median value, for the corresponding day of the week, during the 5- week period Jan 3–Feb 6 2020. We cross-validate the Google mobility data using the MTI data to run the same models and we find the estimations are consistent using the different datasets (See Appendix O).

We 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

[2] 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.

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

[4] The goal providing such reports is to help public health officials make better policies. The dataset is available for downloading at: https://www.google.com/covid19/mobility/?hl=en.

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.[5] See the descriptive statistics of the data in Appendix A.

2.3. Exploratory data analysis

Fig. 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 based on the MTI mobility data. 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.[6] We plot the two curves of social distancing index by computing the daily average for each group respectively.

Fig. 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. Our mapping of the distribution of the social distancing index and distribution of income of counties (See Appendix G) suggests that there is a high degree of correlation between the two. The majority of counties that practice worse social distancing are the counties that tend have larger lower income households. We argue that lower-income group are more likely to have to leave home for work.

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

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.

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 H 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. Fig. 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.

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 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.

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

[6] See the distribution of relative personal income of counties in the US in Appendix F. 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.

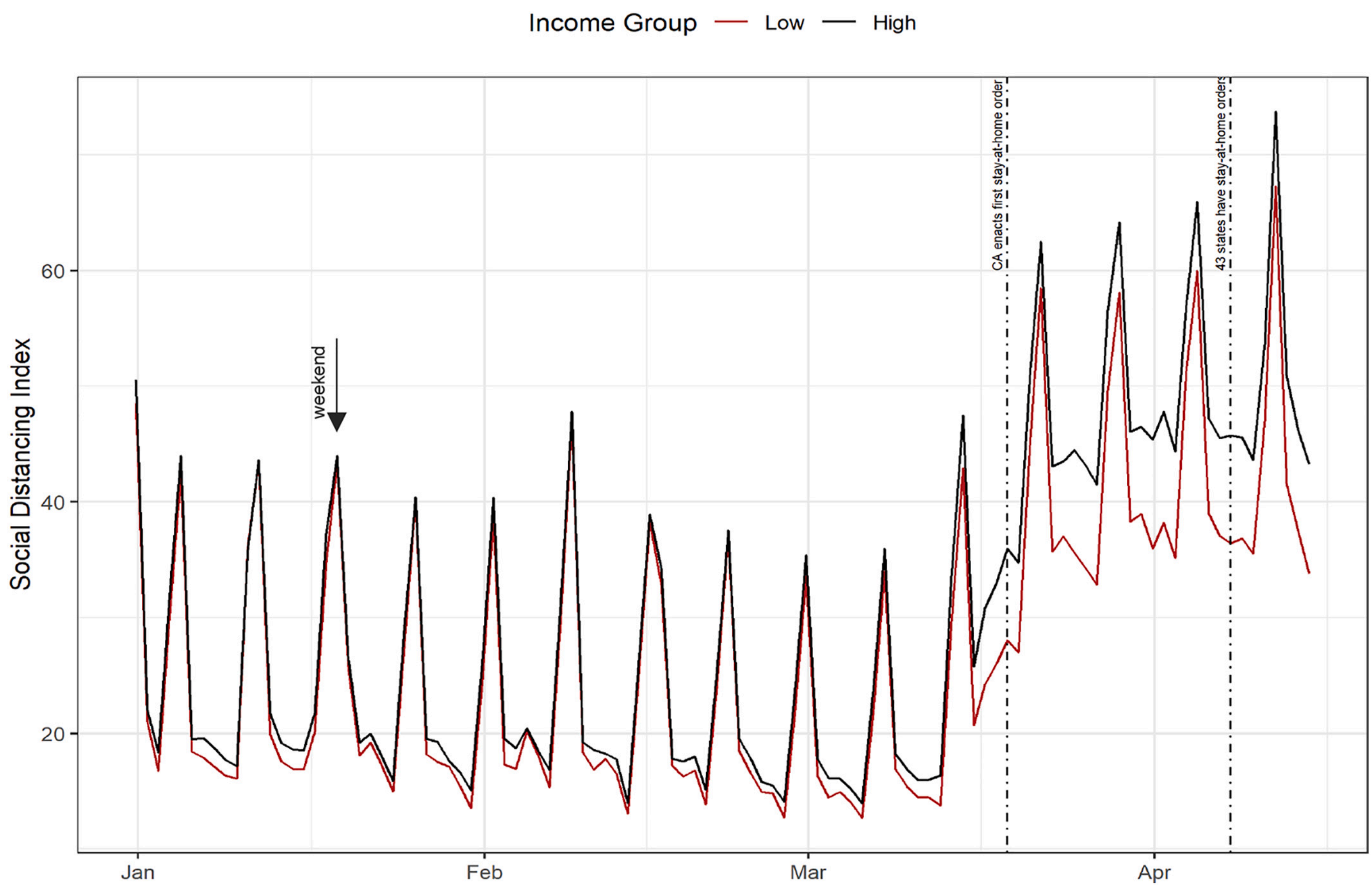

Fig. 1. Social Distancing Index Evolution between Lower- and Upper-income Groups. Social distancing patterns begin diverging between the lower-income and upper-income groups after states start enacting stay-at-home orders. The major difference between the two groups occurs during weekday periods. Data source: Maryland Transportation Institute (2020).

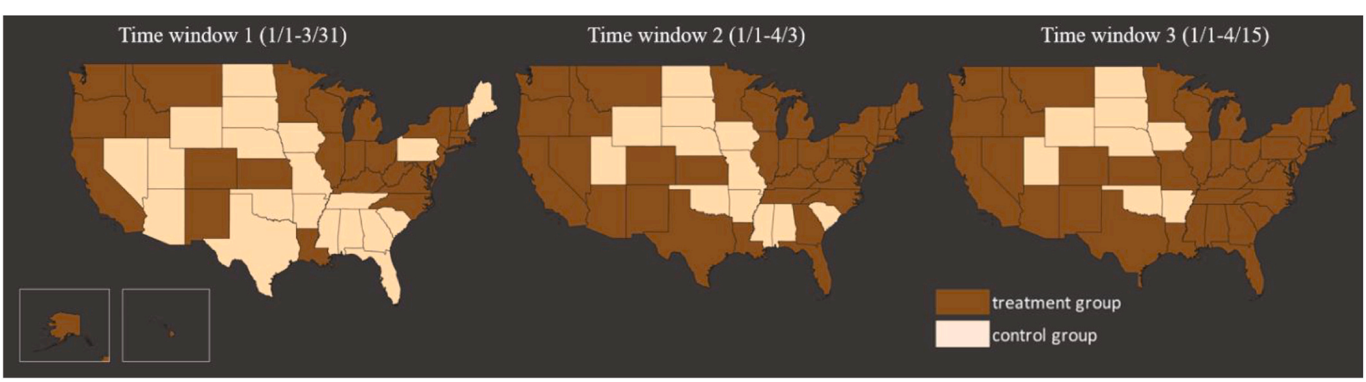

Fig. 2. The control groups in three different time windows (January 1, 2020-March 31, 2020; January 1, 2020-April 3, 2020; January 1, 2020-April 15, 2020). The control groups are defined as the regions without the stay-at-home orders.

The 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 significant differential trends in the pre-treatment period between the control and treatment groups in any of the time windows (See Appendix C). In addition, we conduct robustness checks by allowing specific time trends for the treatment and control groups, respectively, following the method conducted by Davis et al. (2014). This approach tests the robustness of our estimations under the influence of unobservable differential trends. Our results are relatively insensitive to including different time trends (See Appendix D), suggesting that the uncontrolled time-varying confounding unobservables have little influence on our estimated treatment effect. It is also worth noting that since the data for each county is time-series, there is potential temporal autocorrelation within a county that may lead to the estimation of a biased standard error (Hausman and Rapson, 2018). Thus, we cluster our standard errors at the county level, allowing for arbitrary correlations between any two observations within the same county (Hausman and Rapson, 2018).

3. Baseline estimation results

Our DDD approach is described by the following regression model:

$$Y_{it} = \gamma + \beta D_{it} + \alpha D_{it} \cdot I_i + \delta V_{it} + \varphi_i + \vartheta_t + \mu_t + \varepsilon_{it} \quad (1)$$

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 Tables 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 Tables 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 (5) in Tables 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, 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.

The impacts of other control variables on the outcome in these models are within our expectations in Tables 1-3. When the temperature is higher and the amount of rainfall and snowfall is smaller, people are more likely to leave home and make more trips. In addition, the daily new COVID-19 cases have a significantly positive effect on people's social distancing. Interestingly, we find that the COVID-19 total cases have a significantly negative effect on people's social distancing while controlling for the daily COVID-19 new cases. This might reflect an adaptation effect when daily new cases stay constant and trips increase relative to the pandemic early days, despite the total number of cases increasing.

One final observation for our modeling is the possible bidirectional causality between the outcome variable of social distancing and the control variables of COVID-19 cases; this would lead to biased estimation. To address this concern, we add lagged variables for COVID-19 cases into our DID and DDD statistic models as a robustness check (See Appendix E). The estimated coefficients of the variables of stay-at-home order are insensitive to the lagged variables of COVID cases, which provides suggestive evidence that the bidirectional causality between outcome and control variables has little influence on our main results.

4. Accounting for potential selection bias

Here, we consider two possible concerns related to 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 may 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 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 I) 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.

5. Understanding the diverse effects between lower and upper-income groups

The overall effect of stay-at-home orders on social distancing between the lower-income and upper-income groups shows a disparity both from statistical and economical perspectives. In this section, we turn to a deeper analysis of potential mechanisms behind the disparate effects by exploring alternative outcome variables and heterogeneous effects across different income intervals. The 2017 county-level personal income per capita in our dataset ranges from \$11,937 to \$233,860, while its 10th percentile is \$31,514 and 90th percentile is \$53,948. So we divide the personal income per capita into eight intervals including "<30 K", "30 K-40 K", "40 K-50 K", "50 K-60 K", "60 K-70 K", "70 K-80 K", and ">90 K". We then apply the following econometric model.

$$\mathrm{Y_{it}} = \gamma + \sum_{j=1}^{j} \beta_j \mathrm{D_{it}} \cdot \text{Income Interval}_j + \delta \mathrm{V_{it}} + \varphi_i + \vartheta_t + \mu_t + \varepsilon_{it} \quad (2)$$

where Y_{it} is the movement measures at time t in county i. Here, we explore six different movement measures, such as work trips, public transit station visits, non-work trips, park visits, retail and recreation visits, grocery and pharmacy visits. D_{it} is the treatment variable, which takes value one when county i is under a stay-at-home order at time t. 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. φ_i controls for individual county fixed effects. ϑ_t is week-of-sample fixed effects. μ_t is day-of-week fixed effects. ε_{it} is an idiosyncratic error term. We cluster our standard errors at the county level.

We also examine the relationship between the percentage of labor forces in essential industries defined by stay-at-home orders and the

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

	Social Distancing Index	Social Distancing Index	% staying at home	Trips per person	Miles traveled per person
	(1)	(2)	(3)	(4)	(5)
Stay-at-home Order	8.83***	14.08***	6.78***	−0.34***	−4.29***
	(0.26)	(0.58)	(0.33)	(0.02)	(0.35)
Stay-at-home Order × Lower-Income		−6.42***	−3.69***	0.13***	1.36***
		(0.62)	(0.34)	(0.02)	(0.38)
Control variables:					
COVID-19 new cases	0.032**	0.031**	0.017**	−0.001**	−0.006**
	(0.013)	(0.013)	(0.006)	(0.0003)	(0.002)
COVID-19 total cases	−0.002***	−0.002***	−0.001***	0.0001**	0.001***
	(0.001)	(0.001)	(0.0004)	(0.00002)	(0.0001)
Max. temperature	−0.127***	−0.126***	−0.054***	0.004***	0.045***
	(0.002)	(0.002)	(0.001)	(0.0001)	(0.003)
Precipitation	2.074***	2.072***	0.866***	−0.068***	−1.28***
	(0.062)	(0.062)	(0.028)	(0.001)	(0.055)
Snow	1.75***	1.76***	0.752***	−0.033***	−1.27***
	(0.07)	(0.07)	(0.031)	(0.002)	(0.067)
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Observations	262,595	262,595	262,595	262,595	262,595
R-square	0.64	0.64	0.36	0.36	0.14
Mean of outcome variable	25.38	25.38	20.65	3.33	43.52

*Note: Standard errors are clustered at the county level, which are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. "Yes" means the fixed effects indicated in the left column are included in the model. We also estimate an additional model using out-of-county trips per person as the outcome, but the R-square for the model is quite low (0.01) and we do not include this model into our baseline results.

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	Miles traveled per person
	(1)	(2)	(3)	(4)	(5)
Stay-at-home Order	8.13***	13.61***	6.27***	−0.33***	−4.60***
	(0.24)	(0.55)	(0.30)	(0.02)	(0.33)
Stay-at-home Order × Lower-Income		−6.72***	−3.57***	0.14***	1.86***
		(0.57)	(0.31)	(0.02)	(0.35)
Control variables:					
COVID-19 new cases	0.031**	0.029**	0.017**	−0.001**	−0.004*
	(0.014)	(0.013)	(0.007)	(0.0003)	(0.002)
COVID-19 total cases	−0.001**	−0.001**	−0.001**	0.0001**	0.0001
	(0.0008)	(0.0008)	(0.0004)	(0.00002)	(0.0001)
Max. temperature	−0.124***	−0.123***	−0.05***	0.004***	0.041***
	(0.002)	(0.002)	(0.001)	(0.0001)	(0.003)
Precipitation	2.11***	2.11***	0.87***	−0.07***	−1.3***
	(0.063)	(0.063)	(0.03)	(0.001)	(0.055)
Snow	1.76***	1.77***	0.75***	−0.03***	−1.3***
	(0.07)	(0.07)	(0.03)	(0.001)	(0.066)
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Observations	271,250	271,250	271,250	271,250	271,250
R-square	0.63	0.64	0.37	0.36	0.15
Mean of outcome variable	25.79	25.79	20.82	3.32	43.19

*Note: Standard errors are clustered at the county level, which are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. "Yes" means the fixed effects indicated in the left column are included in the model. We also estimate an additional model using out-of-county trips per person as the outcome, but the R-square for the model is quite low (0.01) and we do not include this model into our baseline results.

income at county level.

5.1. Work related trips

We first look at the role that work-related behavior plays in the response to stay-at-home orders during the COVID-19 across socioeconomic groups. Fig. 3 (a) shows the estimated policy effects of stay-at-home orders on per person work trips using the observations in time window 1 (Jan 1, 2020 to March 31, 2020). The results indicate that the stay-at-home orders do not significantly reduce work-related trips for the very low-income group (personal income per capita < \$30 K). The effects of the stay-at-home policy on work trips increases with income until income reaches about 90 K per capita. Upper income groups are more likely to reduce their work trips under stay-at-home orders.

The relatively weak effect of the stay-at-home order on the highest income group's (personal income per capita > \$90 K) work trips could be due to voluntary shelter-in-place behavior. Wealthier households have much more flexibility in terms of travel (Sanchez et al., 2003). Our model suggests that wealthier households were more likely and more able to voluntarily stay at home as the confirmed COVID-19 cases increased even without the effect of stay-at-home orders. Because our model has excluded the "panic effect" and wealthier households could

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	Miles traveled per person
	(1)	(2)	(3)	(4)	(5)
Stay-at-home Order	7.23***	12.92***	5.86***	−0.31***	−4.03***
	(0.22)	(0.48)	(0.26)	(0.01)	(0.30)
Stay-at-home Order × Lower-Income		−6.95***	−3.68***	0.16***	2.25***
		(0.49)	(0.27)	(0.01)	(0.29)
Control variables:					
COVID-19 new cases	0.018**	0.016**	0.001***	−0.0005**	−0.003**
	(0.008)	(0. 007)	(0. 004)	(0. 007)	(0. 001)
COVID-19 total cases	−0.0002***	−0.0003***	−0.0001***	7.21e-06***	0.00003*
	(0. 00007)	(0. 00006)	(0. 00004)	(1.98e-06)	(0. 00002)
Max. temperature	−0.125***	−0.123***	−0.051***	0. 004***	0.043***
	(0. 002)	(0. 002)	(0. 001)	(0. 00008)	(0. 003)
Precipitation	1.935***	1.906***	0.785***	−0.060***	−1.054***
	(0. 067)	(0. 66)	(0. 031)	(0. 002)	(0. 051)
Snow	1.935***	1.703***	0.743***	−0.032***	−1.216***
	(0. 069)	(0. 069)	(0. 032)	(0. 002)	(0. 065)
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Observations	305,870	305,870	305,870	305,870	305,870
R-square	0.67	0.68	0.41	0.39	0.21
Mean of outcome variable	27.97	27.97	21.66	3.27	41.67

*Note: Standard errors are clustered at the county level, which are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. "Yes" means the fixed effects indicated in the left column are included in the model. We also estimate an additional model using out-of-county trips per person as the outcome, but the R-square for the model is quite low (0.01) and we do not include this model into our baseline results.

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	0.058***	0.159**	0.052***	0.151***	0.042***	0.127***
	(0.016)	(0.072)	(0.009)	(0.044)	(0.011)	(0.021)
COVID-19 total cases	0.011***	0.052*	0.005*	0.037**	0.002***	0.016***
	(0.003)	(0.030)	(0.003)	(0.016)	(0.0003)	(0.003)
Max. temperature	−0.124***	−0.119***	−0.120***	−0.115***	−0.118***	−0.116***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Precipitation	2.020***	2.070***	2.068***	2.122***	1.824***	1.861***
	(0.063)	(0.066)	(0.064)	(0.066)	(0.066)	(0.067)
Snow	1.977***	1.753***	1.991***	1.773***	1.921***	1.702***
	(0.073)	(0.074)	(0.073)	(0.074)	(0.070)	(0.073)
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. "Yes" means the fixed effects indicated in the left column are included in the model.

have a larger "panic response", the effect of stay-at-home order on the highest income group could be weaker.

We also used the Google Community Mobility Report data to study transportation patterns, specifically the relationship between the effects of stay-at-home orders on the transit station visits and personal income per capita. Fig. 3 (b) shows that transit station visits for the very low-income group (personal income per capita < \$30 K) actually increase after implementation of stay-at-home orders. It is likely that the very low-income group still relied on transit for work related trips (See the detailed explanation in Appendix K). Transit station visits fell sharply for the upper-income group. We find this result is consistent with other public transportation studies showing that low-income households place greater reliance on public transportation, and travel intensity declined less among lower-income group (Brough et al., 2020; Glaeser et al., 2008).

For a deeper understanding of the results of this analysis, consider first, that under the stay-at-home orders, "essential" businesses remained 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

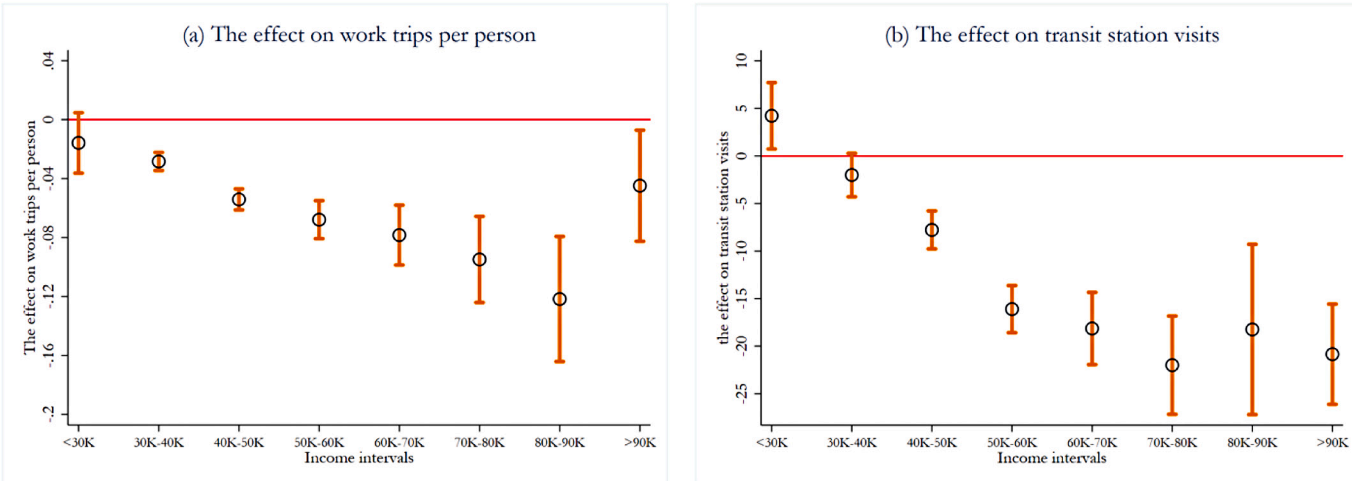

Fig. 3. The effect of the stay-at-home orders on work-related activities across income (a) the effects on work trips per person across different income levels. (b) the effects on transit station visits across different income levels. Black circles are point estimates, while error bars are 95th percentile confidence intervals. We use observations in time window (01/01/2020–03/31/2020) to fit the model in plot (a), and observations in time window (02/15/2020–03/31/2020) to fit the model in plot (b).

transportation sector (See Appendix J). Within the essential businesses, all sectors except the medical and financial sectors have relatively low wages (Appendix J). Workers with lower-wages account for about 76% of all employment in essential businesses. During the COVID-19 pandemic, the demand for some sectors of essential businesses has greatly increased (Tomer and Kane, 2020).

To capture the relationship between the labor force in essential businesses and personal income per capita, we collected data on essential businesses from a wide range of definitions. Due to the lack of a universal definition of essential businesses, our effort attempts to cover a broad range of industries and activities that can reflect a broader picture of the essential businesses. We strategically include five definitions of the essential industries, which are coded at the level of four-digit North American Industry Classification System (NAICS). We believe that the four-digit-code industry system is detailed enough to capture the dynamics and dimensions of the different industries and activities. See the detailed five definitions of the essential industries in Appendix L.

We present the results in Fig. 4 to show the relationship between the percentage of labor force in essential industries and the relative income (the ratio of a county's personal income per capita to the personal income per capita of the state to which it belongs) at county level. All the five scenarios consistently show a significant negative correlation between the percentage of labor force in essential industries and income (See Appendix M). This indicates that the percentage of labor force in the essential industries is declining as income increases in that county. Of course, as more industries are included in the definition of essential

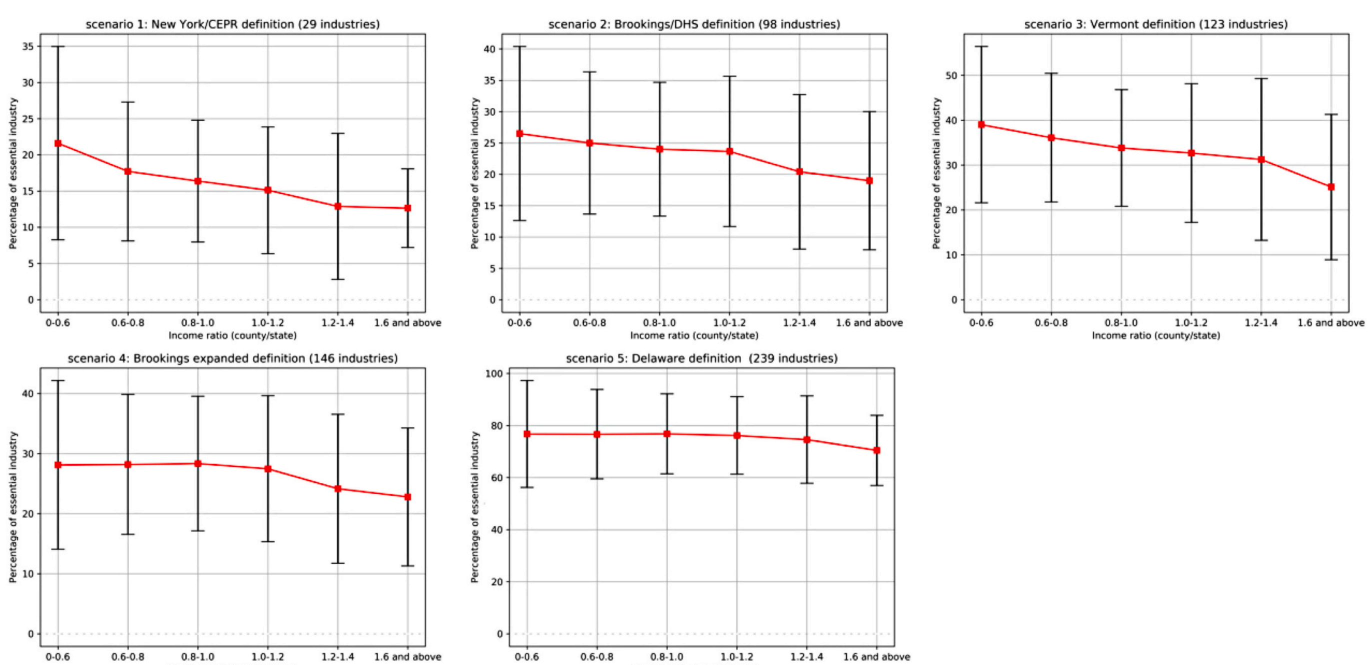

Fig. 4. Percentage of labor forces in essential businesses across income groups at county level. We have adjusted the labor force based on their percentage of workers who could work at home by industry (the data is from the 2019 Department of Labor). We also specified an unadjusted run, and the results are similar. The error bars are standard deviations. The income ratio 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.

businesses, the negative correlation has less effect. These results serve as supporting evidence that the disparity in social distancing between the lower-income and upper-income groups can be partially explained by work-related trips due to the essential businesses.

5.2. Non-work-related trips

We now turn to the role that non-work-related activities plays in the response of social distancing patterns to stay-at-home orders. Fig. 5 (a) shows the estimated policy effects of stay-at-home orders on non-work trips per person by personal per capita income. The results indicate that the stay-at-home orders do not significantly reduce non-work trips for the very low-income group (personal income per capita < $30 K). The effects of the stay at home policy increase as income increases until income is about 90 K per capita. Upper income groups are more likely to reduce their non-work trips under stay-at-home orders.

We further decompose the effects of stay-at-home orders on non-work activities into the three categories: park visits, retail and recreation visits, and grocery and pharmacy visits in Fig. 5 (b) – (d). We find thatboth the lower-income and upper-income groups reduce retail and recreation visits, and grocery and pharmacy visits after the implementation of stay at-home-orders, with the upper-income group reducing trips statistically more compared to the lower-income group. Upper income groups have the luxury of placing online orders to avoid the risk of non-work trips. Interestingly, upper-income households do not reduce park trips; this trend is notable when personal income per capita is between $60 K and $90 K.

One 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 3140, which is large enough to reflect differences among counties. Second, within each state, economic inequality is evident among counties as we show in Appendix F. The range of relative personal income[7] 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 be high in the county. To further address this concern, we also conduct another robustness check using the SafeGraph dataset at the census tract level (See Appendix P). The results of the robustness check are consistent with our main results.

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 resulting from 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 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, by including the Google Community Mobility data, we find that the effects of the stay-at-home orders on the lower-income group's mobility, including both work-related and non-work-related activities, are 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 for the very low-income (personal income per capita < $30 K), and the orders can even significantly increase this group's transit station visits, while reducing middle- and perhaps high-income work trips. In terms of non-work-related mobility activities, we find that the stay-at-home orders significantly reduce non-work mobility for middle- and high-income groups, with the exception of park visits. However, the orders do not reduce per person non-work trips and retail and recreation visits for the very low-income (personal income per capita < $30 K).

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.

Less 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 create inequities. 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 underlying fundamentals related to socioeconomic status and social support, particularly where there already exists 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, for example, 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, access to health care services, grocery stores, job opportunities, etc., amplify the negative consequences of wealth disparity (van 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 (van Dorn et al., 2020), and we are all affected by the burdens we place on vulnerable communities.

There are ways we can reduce the negative effects on vulnerable

[7] 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.

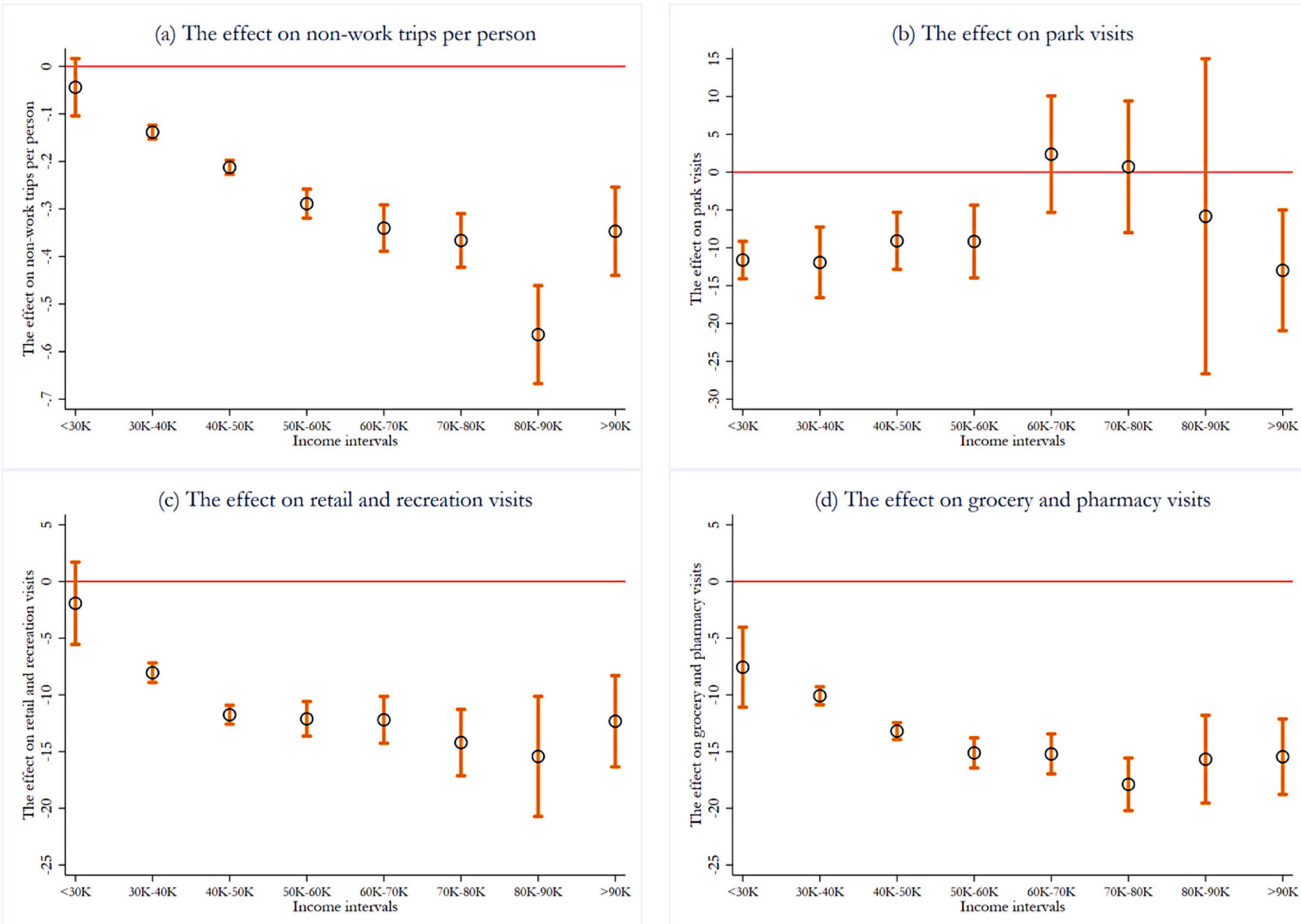

Fig. 5. The effect of the stay-at-home orders on non-work activities across income (a) the effects on non-work trips per person. (b) the effects on park visits. (c) the effects on retail and recreation visits. (d) the effects on grocery and pharmacy visits. Black circles are point estimates while error bars are 95th percentile confidence intervals. We use observations in time window (01/01/2020–03/31/2020) to fit the model in plot (a), and observations in time window (02/15/2020–03/31/2020) to fit the model in plot (b) (c) (d).

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 more than five months since the first stay-at-home order was initiated in the Washington State. We only see delayed efforts in prioritizing the health or safety of these workers. We only see one bill passed by the House in May, which aims to give a raise to essential workers through the Hazard Pay in the HEROES Act. However, its 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 June, there were 18 million jobless Americans with a high unemployment rate of 11.1 (BLS, 2020). Unemployment will likely remain elevated even after the COVID-19 runs its course. The newly released IMF special report forecasts a −4.9% contraction in 2020 for the global economy, which is much worse than the financial crisis in 2008 (IMF, 2020a, 2020b). While in the United States, due to the response to the COVID-19 pandemic, the real GDP decreased 4.8% 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% to 38% (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).

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.

Funding

Partial funding for this research was provided by the National Science Foundation under CMMI-2027678.

Acknowledgements

We are thankful to Yueming (Lucy) Qiu and Nathan Hultman for comments that substantially improved the paper. We would like to acknowledge that the University of Maryland COVID-19 Impact Analysis Platform, created by the Maryland Transportation Institute, provides the online comprehensive national human mobility dataset for this study. Detailed information for this platform can be found at: www.data.covid.umd.edu

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	118,302	–
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	41,973.64	11,565.5	11,937	233,860	2017$

Appendix 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	6,335,733 (7064760)	6,009,481 (6925749)	0.05	7,490,125 (7763612)	3,216,498 (1912608)	0.75	6,879,505 (7386678)	2,148,717 (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	33,957 (4975)	31,579 (5977)	0.43	34,044 (5662)	29,821 (2861)	0.94	32,398 (5688)	30,120 (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

(continued on next page)

Table B (*continued*)

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.
Land area	67,639.91 (95,106.54)	70,870.06 (51,030.59)	−0.04	70,072.28 (96,397.89)	65,906.88 (19,666.11)	0.06	68,284.12 (87,470.26)	72,173.28 (14,394.48)	−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).

Appendix 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. Fig. A 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).

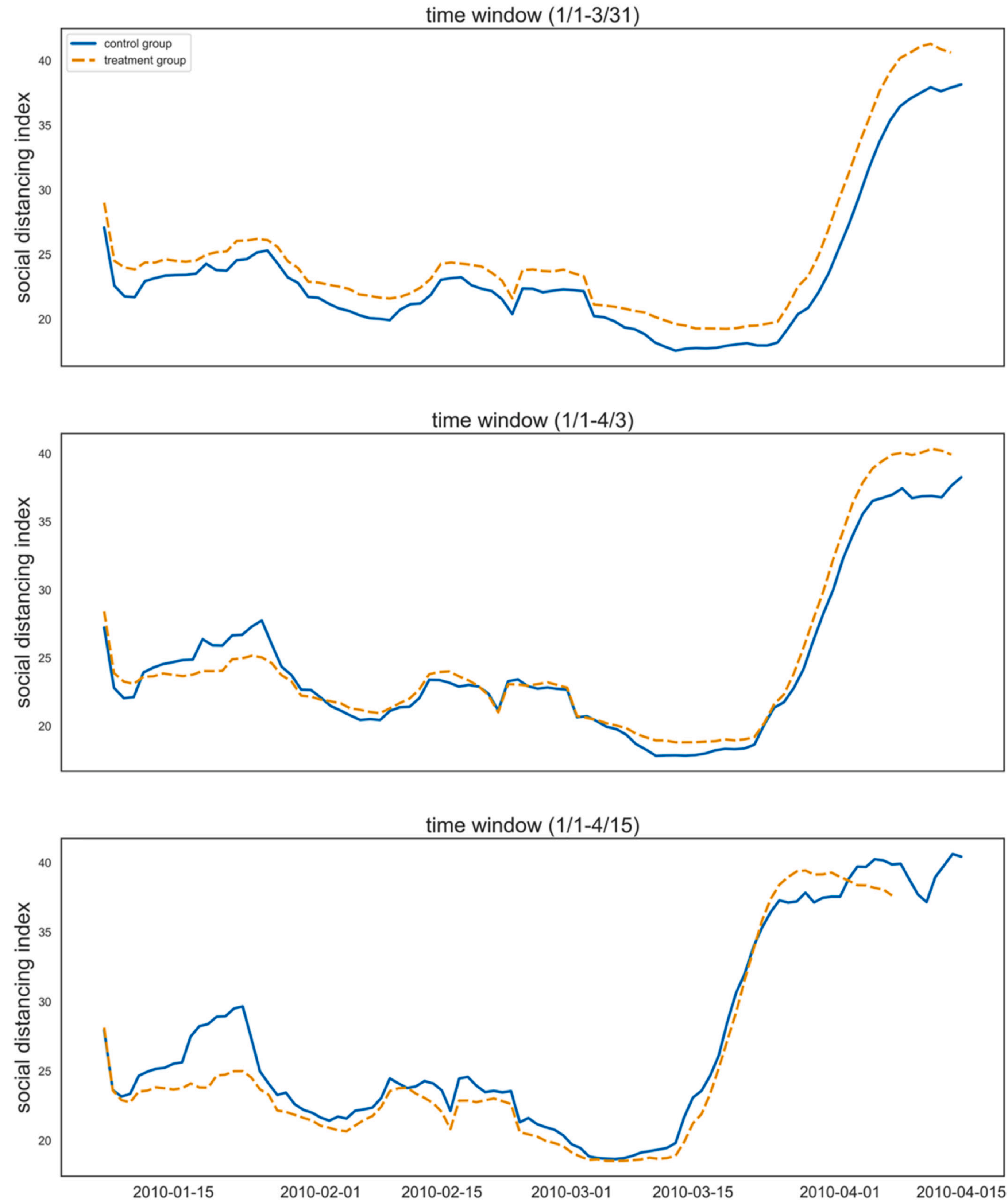

Fig. A. The pre-treated trends between the control group and the treatment group. The pre-treated trends between the treatment and control groups are generally parallel in all time windows, with evidence of a greater number of parallel trends in window 1. Note also a period of rapid growth after the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

Appendix D. Alternative robustness checks for differential trends

We conduct robustness checks by allowing specific time trends for the treatment and control groups, respectively, following the method conducted by Davis et al. (2014). We add interaction terms between the treatment group indicator variable and time trend variables (the number of days in our sample) into our baseline model. We tried a linear time trend, quadratic time trend, and cubic time trend respectively. The following Eq. (D2) represents this approach, while the Eq. (D1) is our baseline DID model. These time trends can control for time-variant systematic differential trends between the treatment and the control groups.

$$Y_{it} = \gamma + \beta D_{it} + \alpha D_{it} \cdot I_i + \delta V_{it} + \varphi_i + \vartheta_t + \mu_t + \varepsilon_{it} \tag{D1}$$

$$Y_{it} = \gamma + \beta D_{it} + \alpha D_{it} \cdot I_i + \delta V_{it} + \varphi_i + \vartheta_t + \mu_t + \boldsymbol{\rho_1 T_i \cdot \gamma_t} + \boldsymbol{\rho_2 T_i \cdot \gamma_t^2} + \boldsymbol{\rho_3 T_i \cdot \gamma_t^3} + \varepsilon_{it} \tag{D2}$$

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. 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. φ_i controls for individual county fixed effects. ϑ_t is week-of-sample fixed effects. μ_t is day-of-week fixed effects. ε_{it} is an idiosyncratic error term. In Eq. (D2), T_i is a treatment group indicator variable, which takes values one for counties in the treatment group. γ_t is the number of days in our sample. We cluster standard errors at the county level.

Table C-E present the estimation results for different time windows (01/01–03/31; 01/01–04/03; 01/01–04/15), respectively. Column (1) is the baseline estimation result by Eq. (D1) without time trend variables, while Column (2)–(4) are the results including different differential time trends by Eq. (D2). The results are relatively insensitive to including different time trends, suggesting that the uncontrolled time-varying confounding unobservables have little influences on our estimated treatment effect.

Table C
The estimation results including time trends in time window 1 (*01/01–03/31*).

	Outcome: Social Distancing Index			
	No time trend	*Linear time trend*	*Quadratic time trend*	*Cubic time trend*
	(1)	(2)	(3)	(4)
Stay-at-home Order	14.08***	13.47***	12.02***	13.3***
	(0.58)	(0.57)	(0.57)	(0.58)
Stay-at-home Order × Lower-Income	−6.42***	−6.42***	−6.39***	−6.44***
	(0.62)	(0.62)	(0.62)	(0.61)
Control variables:				
COVID-19 new cases	Yes	Yes	Yes	Yes
COVID-19 total cases	Yes	Yes	Yes	Yes
Max. temperature	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Snow	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Treatment group dummy× linear time trends	No	Yes	Yes	Yes
Treatment group dummy× quadratic time trends	No	No	Yes	Yes
Treatment group dummy× cubic time trends	No	No	No	Yes
Observations	262,595	262,595	262,595	262,595
R-square	0.64	0.64	0.64	0.62

*Note: Standard errors are clustered at the county level, which are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. "Yes" means the control variables and fixed effects indicated in the left column are included in the model.

Table D
The estimation results including time trends in time window 2 (*01/01–04/03*).

	Outcome: Social Distancing Index			
	No time trend	*Linear time trend*	*Quadratic time trend*	*Cubic time trend*
	(1)	(2)	(3)	(4)
Stay-at-home Order	13.61***	12.95***	11.52***	12.74***
	(0.55)	(0.54)	(0.54)	(0.55)
Stay-at-home Order × Lower-Income	−6.72***	−6.72***	−6.70***	−6.74***
	(0.57)	(0.57)	(0.58)	(0.57)
Control variables:				
COVID-19 new cases	Yes	Yes	Yes	Yes
COVID-19 total cases	Yes	Yes	Yes	Yes
Max. temperature	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Snow	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes

(*continued on next page*)

Table D (*continued*)

	Outcome: Social Distancing Index			
	No time trend	*Linear time trend*	*Quadratic time trend*	*Cubic time trend*
	(1)	(2)	(3)	(4)
Day-of-week FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Treatment group dummy× linear time trends	No	Yes	Yes	Yes
Treatment group dummy× quadratic time trends	No	No	Yes	Yes
Treatment group dummy× cubic time trends	No	No	No	Yes
Observations	271,250	271,250	271,250	271,250
R-square	0.64	0.64	0.64	0.62

*Note: Standard errors are clustered at the county level, which are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. "Yes" means the control variables and fixed effects indicated in the left column are included in the model.

Table E
The estimation results including time trends in time window 3 (*01/01–04/15*).

	Outcome: Social Distancing Index			
	No time trend	*Linear time trend*	*Quadratic time trend*	*Cubic time trend*
	(1)	(2)	(3)	(4)
Stay-at-home Order	12.92***	12.61***	11.65***	12.8***
	(0.48)	(0.46)	(0.47)	(0.47)
Stay-at-home Order × Lower-Income	−6.95***	−6.95***	−6.95***	−6.94***
	(0.49)	(0.49)	(0.49)	(0.48)
Control variables:				
COVID-19 new cases	Yes	Yes	Yes	Yes
COVID-19 total cases	Yes	Yes	Yes	Yes
Max. temperature	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Snow	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Treatment group dummy× linear time trends	No	Yes	Yes	Yes
Treatment group dummy× quadratic time trends	No	No	Yes	Yes
Treatment group dummy× cubic time trends	No	No	No	Yes
Observations	305,870	305,870	305,870	305,870
R-square	0.68	0.68	0.68	0.66

*Note: Standard errors are clustered at the county level, which are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. "Yes" means the control variables and fixed effects indicated in the left column are included in the model.

Appendix E. Robustness checks by including lagged variables of COVID cases

There is a bidirectional causality between the outcome variable of social distancing and the control variables of COVID cases. The bidirectional causality may cause the coefficients of the COVID cases variables biased. However, the variables of COVID cases are control variables, while our independent variables of interest are the adoption of stay-at-home orders and the interaction term between the adoption variable and income variable. The bidirectional causality between outcome and control variables has little influence on the estimation of our core independent variables, because the adoption of stay-at-home order was mainly driven by the severer pandemic not people's trip characteristics.

To further address this concern of bidirectional causality, we add lagged variables of the COVID cases into our DID and DDD statistic models to improve model fit. We add 20 lagged variables including one day to ten days lagged variables of daily new cases and one day to ten days lagged variables of accumulative cases. Table F presents the estimations after adding the lagged variables. The estimations on the variables of our interest are insensitive to including the lagged variables of COVID cases, which provides suggestive evidence that the bidirectional causality between outcome and control variables has little influence on our main results.

Table F
The estimations using DID and DDD models including lagged variables of COVID cases.

	Outcome: Social distancing index					
	Time window 1		Time window 2		Time window 3	
	(1)	(2)	(3)	(4)	(5)	(6)
Stay-at-Home Order	8.52***	13.56***	7.88***	13.24***	7.03***	12.62***
	(0.26)	(0.6)	(0.24)	(0.55)	(0.22)	(0.47)
Stay-at-Home Order × Lower-Income		−6.14***		−6.57***		−6.83***
		(0.62)		(0.57)		(0.48)
Control variables:						
COVID-19 new cases	Yes	Yes	Yes	Yes	Yes	Yes

(*continued on next page*)

Table F (*continued*)

	Outcome: Social distancing index					
	Time window 1		Time window 2		Time window 3	
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 accumulative cases	Yes	Yes	Yes	Yes	Yes	Yes
Lags of COVID-19 new cases	Yes	Yes	Yes	Yes	Yes	Yes
Lags of COVID-19 accumulative cases	Yes	Yes	Yes	Yes	Yes	Yes
Daily maximum temperature	Yes	Yes	Yes	Yes	Yes	Yes
Daily 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	233,735	233,735	242,390	242,390	277,010	277,010
R-square	0.67	0.67	0.67	0.67	0.69	0.7

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at county level, which are in parentheses. "Yes" means the control variables and fixed effects indicated in the left column are included in the model. We include one day to ten days lagged variables of COVID-19 new cases and accumulative cases into the models.

Appendix F. 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 Fig. B, 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 3140, 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 Fig. B. 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.

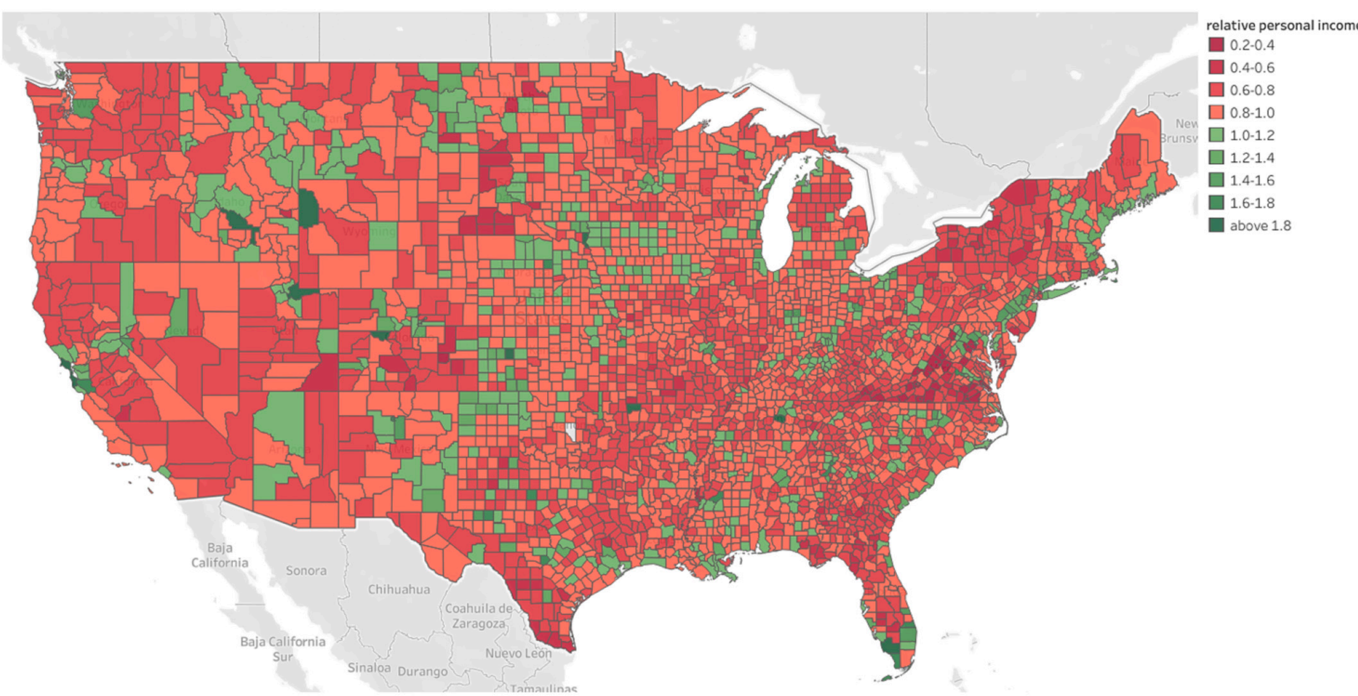

Fig. B. The distribution of relative personal income of counties in the United States.

Appendix G. The distribution of social distancing index and personal income of counties

We map out the distribution of social distancing index (averages from 01/01/2020 to 04/15/2020, see Fig. C) and distribution of county income ($ in 2018, see Fig. D). The two maps are highly correlated with each other. The majority of counties that practice worse social distancing in Fig. C are these counties that have lower income in Fig. D.

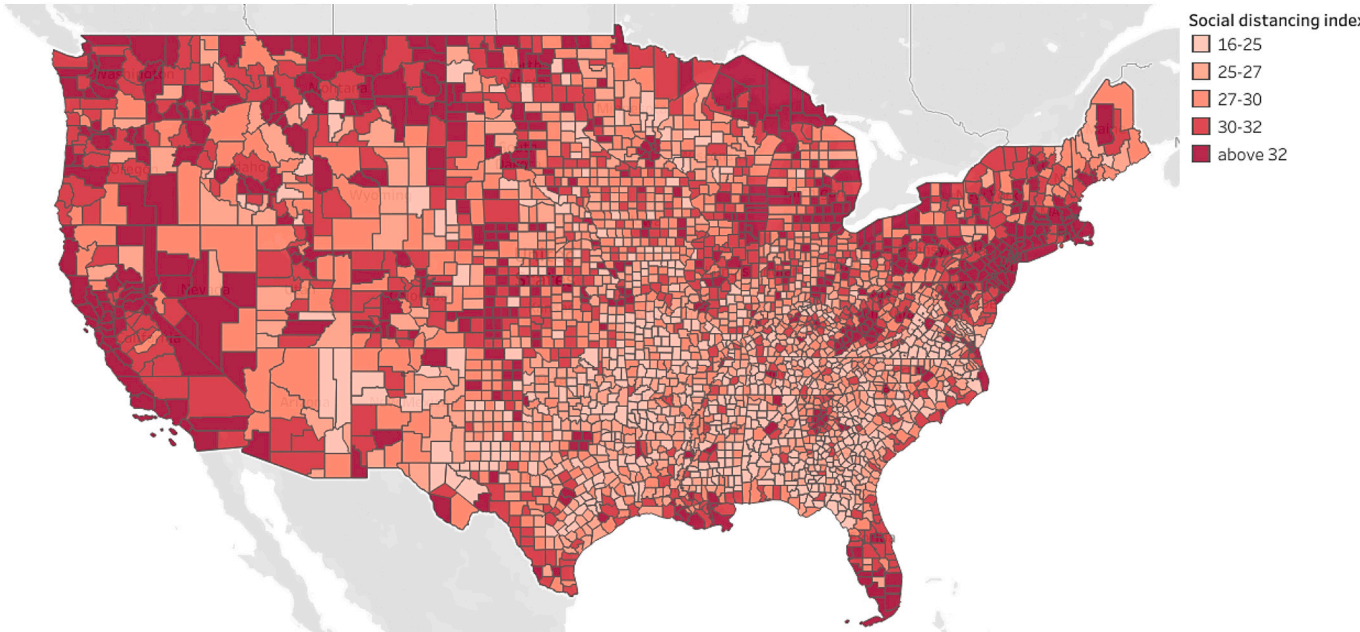

Fig. C. The distribution of social distancing index (averages from 01/01/2020 to 04/15/2020) of counties in the United States (note: the method of categorization is based on equal counts per quantile).

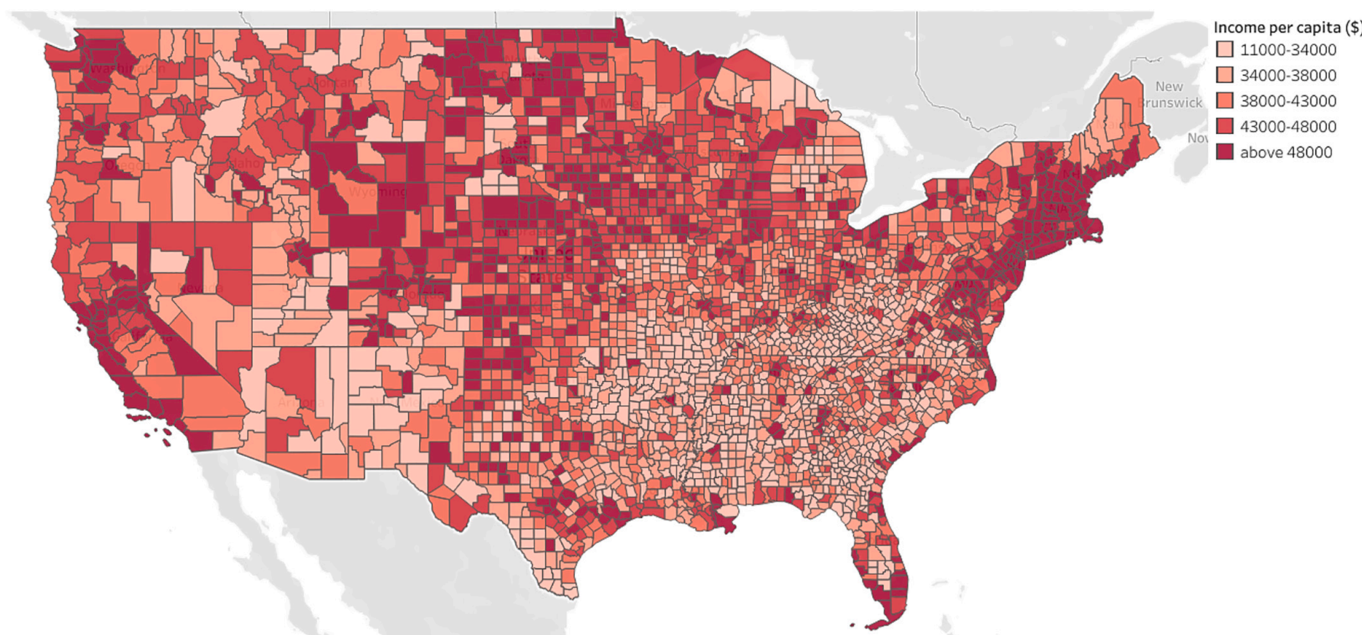

Fig. D. The distribution of personal income per capita of counties in the United States (note: the method of categorization is based on equal counts per quantile).

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

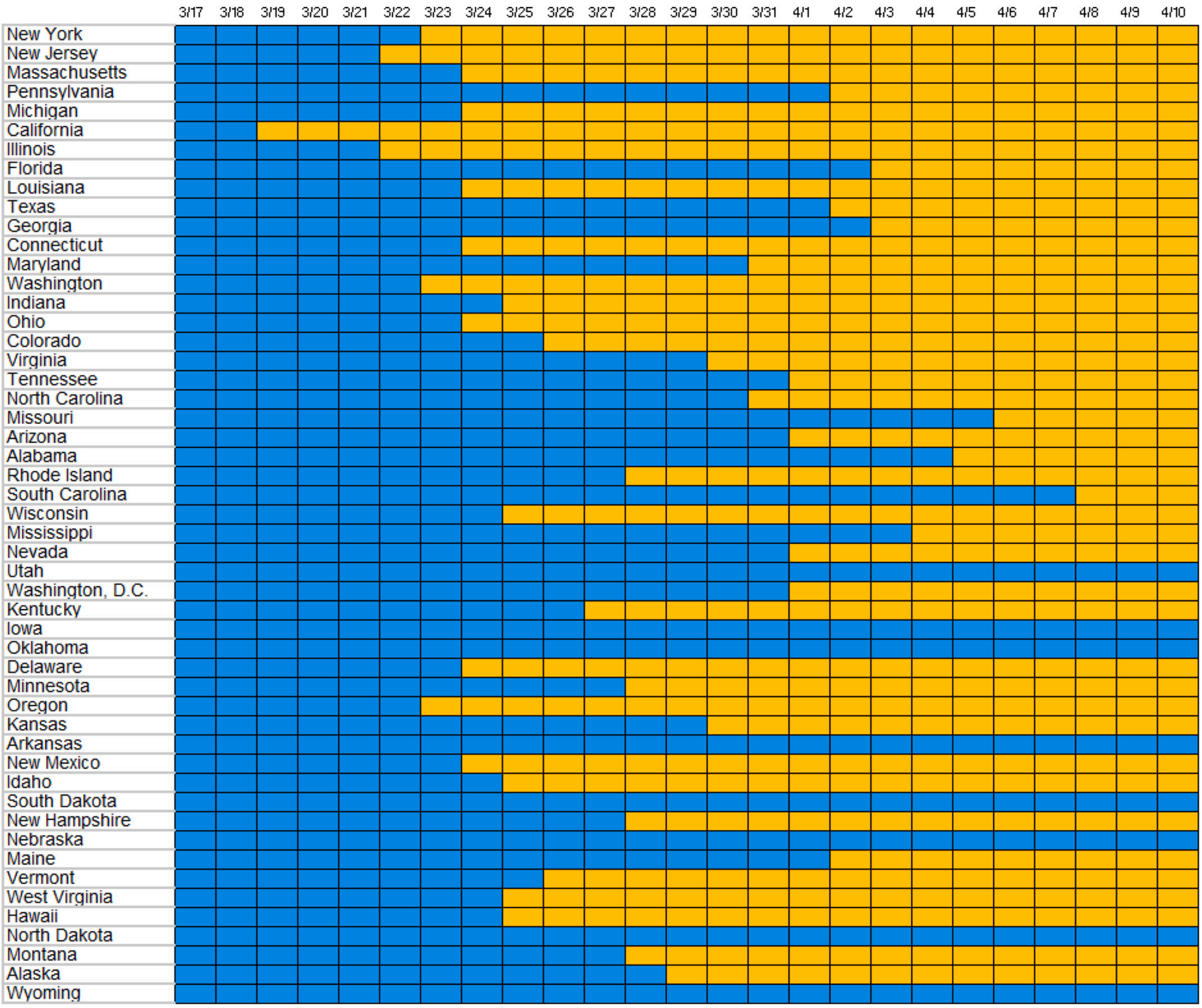

Fig. E. The issued dates of state-wide stay-at-home orders in the United States. Yellow blocks represent the effective dates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Appendix I. The distribution of highly populated counties

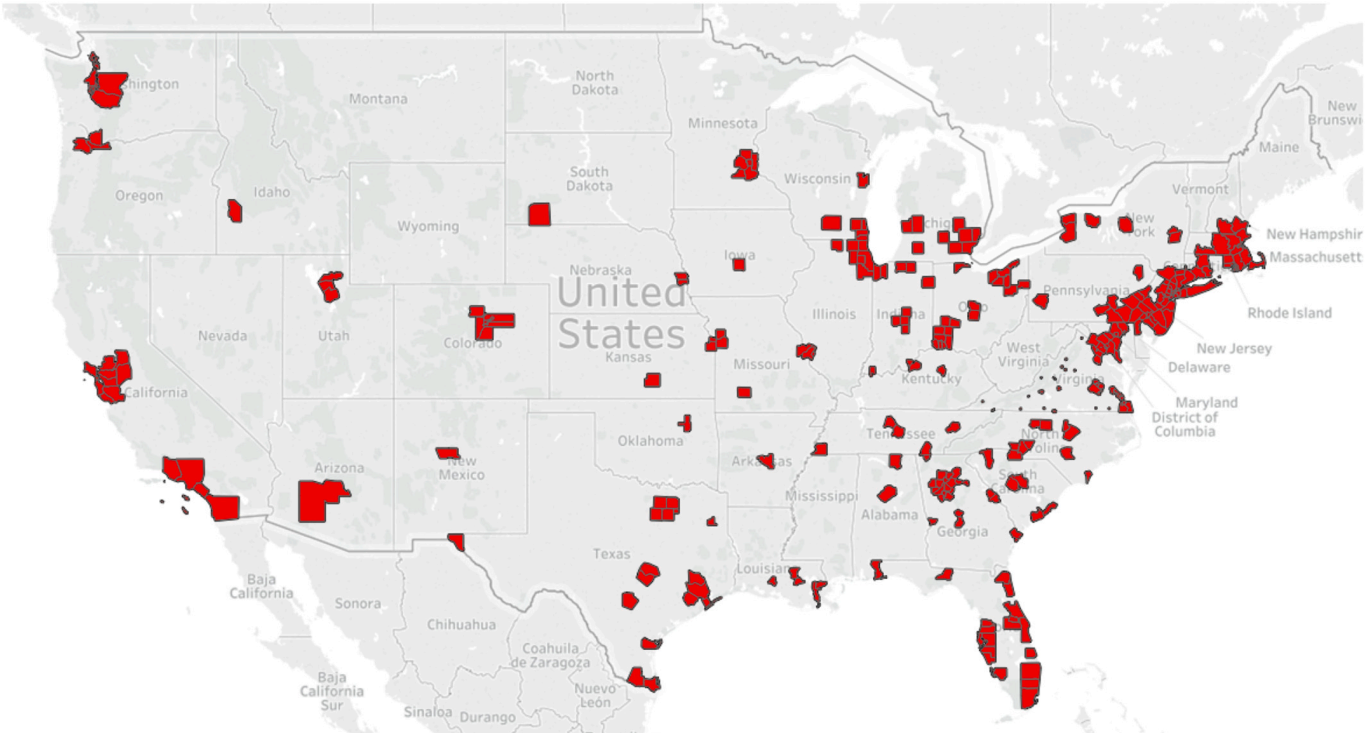

Fig. F. The distribution of highly populated counties (top 10% of counties in population density).

Appendix J. Table of Essential business

Table G
Table of Essential business.

Essential business	Sub-category	Hourly rate	Annual rate	Employment	Employment per 1000 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[a]	\$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.
[a] This data is from May 2018 National Industry-Specific Occupational Employment and Wage Estimates, Sectors 44 and 45 - Retail Trade.

Appendix K. The increased visits to public transit stations among the low-income group (⟨30*K*)

The increased visits to public transit stations among the low-income group (<30 K) could be caused by the increased trips to work places via public transportation. Lower income groups are more likely to take the public transportation, such as subway, railway, and shuttle bus, to work places. During the COVID-19 pandemic, the demand for some of the essential businesses is increased. For instance, more people would like to choose delivery services to get grocery and daily necessities, so the demand for warehouse keepers and distribution workers, couriers and deliverymen/women could be increased. Thus, a large number of workers in essential businesses, most of whom come from the lower-income group, still leave home and work after the implementation of stay-at-home orders. For instance, Fig. G plots Walmart's daily total frequency and amount of online and in-store transactions in the U.S. from 2019 to 2020. The online transaction frequency and amount at Walmart in April 2020 were significantly higher compared to the same period last year, while the in-store transaction frequency and amount were roughly the same as the same period last year. In total, the transaction in Walmart was increased indicating that the demand for the workers, most of whom are lower-income, could also increase during the pandemic.

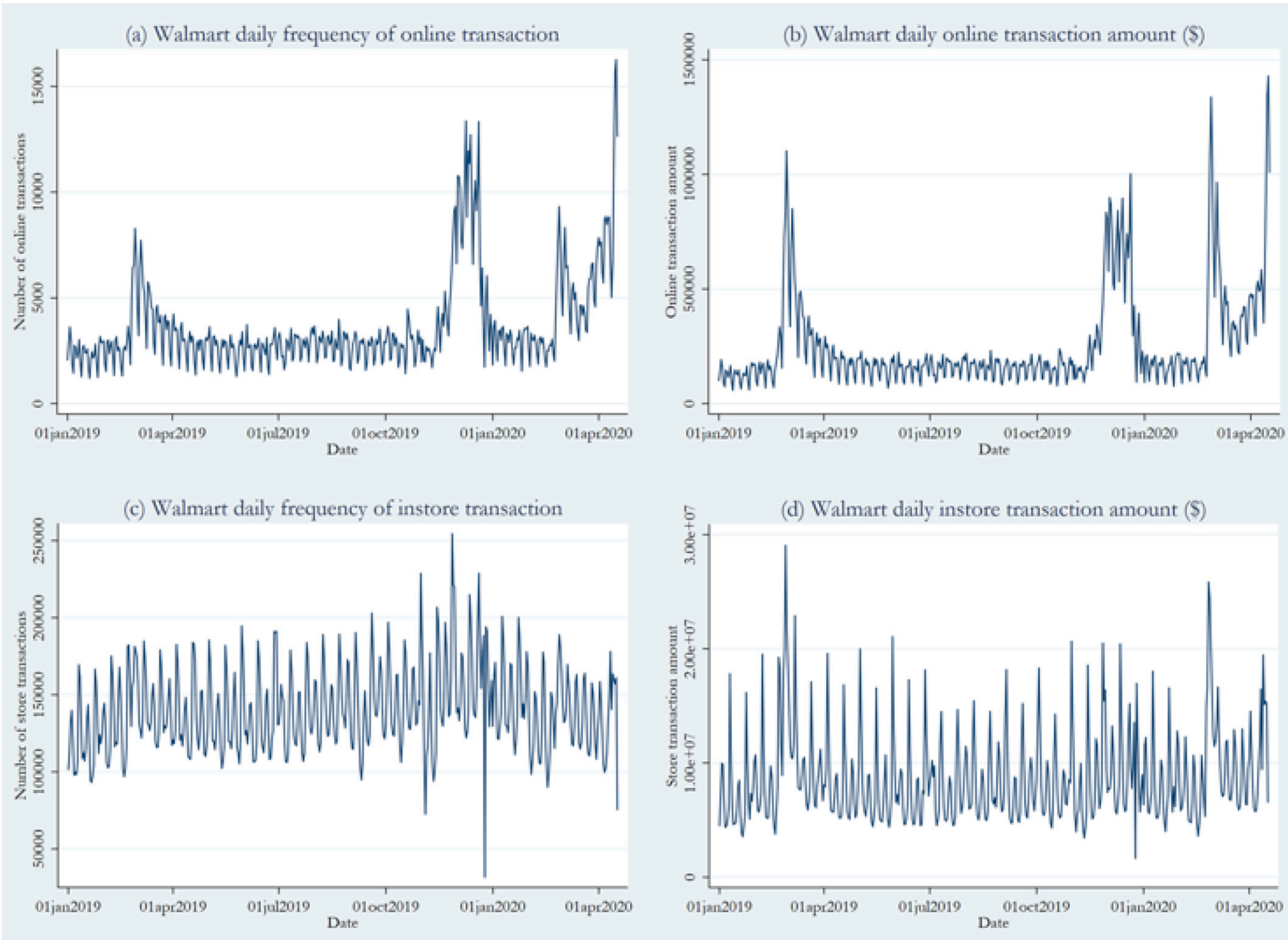

Fig. G. Walmart's daily total frequency and amount of online and in-store transactions in the U.S. from 2019 to 2020 (Data source: SafeGraph COVID-19 Data Consortium, https://www.safegraph.com/covid-19-data-consortium).

Appendix L. The detailed five definitions of the essential industries

The definitions we adopted are: 1) "frontline workers" defined by the New York Cities Controller (New York City, 2020) and Center for Economic and Policy Research (CERP, 2020); 2) Brookings's two definition of the frontline works, one strictly follows the definition of Department of Homeland Security (DHS), the other is the expanded version by their own expert judgement (Tomer and Kane, 2020); 3) State of Vermont (State of Vermont, 2020); 4) State of Delaware (State of Delaware, 2020). We believe that the definition adopted by the state of Delaware is the broadest one, because it captures roughly 80% of the total industries. We rank the five scenarios based on the number of industries they host. Thus, the range of industries in these five scenarios are from 29 to 239.

Appendix M. The correlation between the percentage of labor force in essential industries and the income

We run the correlation analysis between the percentage of labor force in essential industries and the income at the county level, and the results are provided in Table H. All the coefficients of the five scenarios are negative with statistically significant.

Table H
The correlation between the percentage of labor force in essential industries and the income.

	Outcome: the relative income									
	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
The percentage of labor force in essential industries	−58.41 (12.10)	***	−44.16 (9.91)	***	−32.11 (7.83)	***	−52.67 (9.60)	***	−48.46 (8.88)	***

(*continued on next page*)

Table H (*continued*)

	Outcome: the relative income				
	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Observation	3139	3139	3137	3139	3137
R-square	0.01	0.01	0.01	0.01	0.01

* Note: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The relative income is the ratio of a county's personal income per capita to the personal income per capita of the state to which it belongs.

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

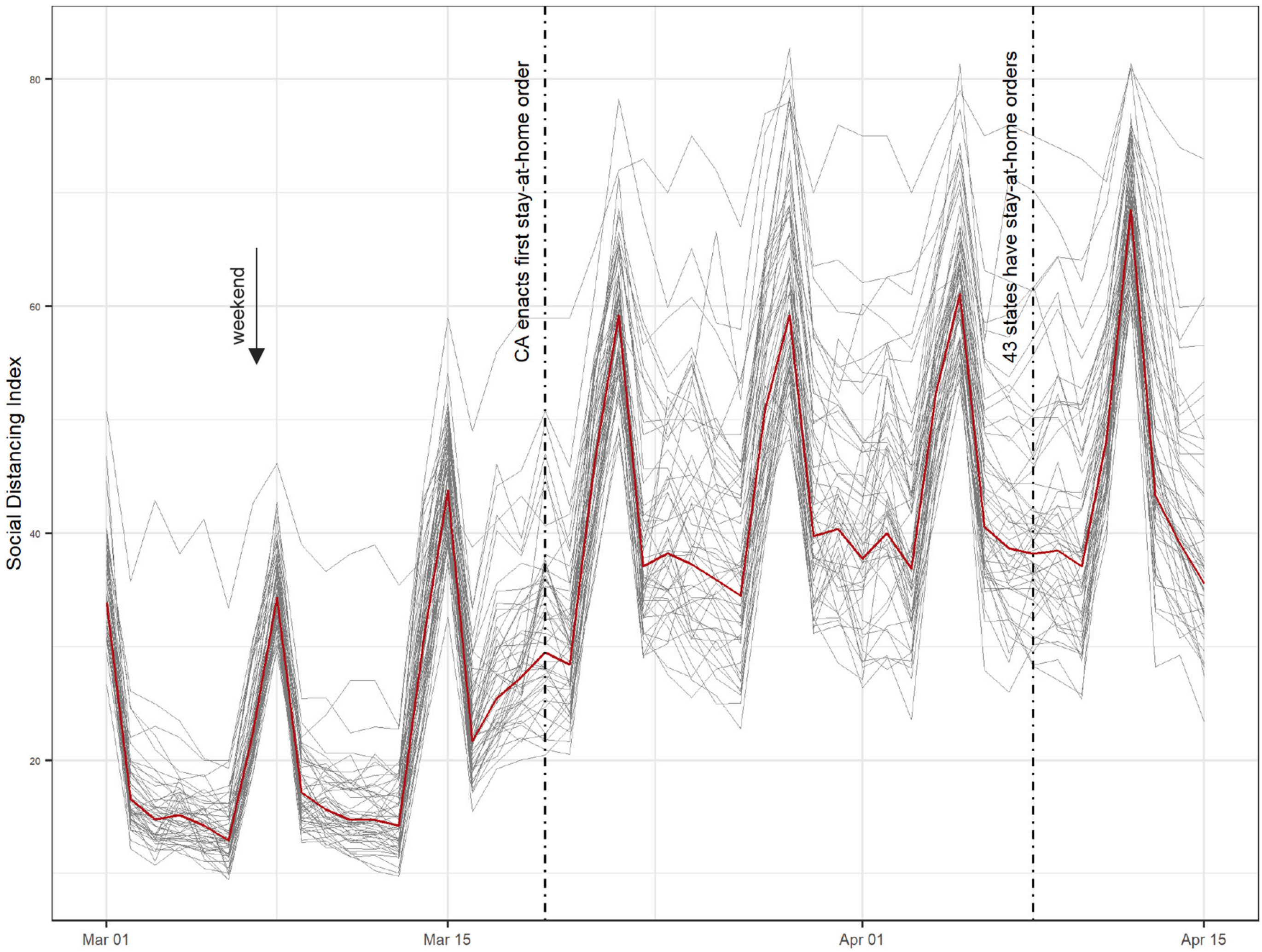

Fig. H. The evolution of the social distancing indices. Gray lines are the social distancing indices of 50 states plus the District of Columbia. The red line is the national average social distancing index. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Appendix O. Cross-validation between the Google and MTI datasets

We cross-validate the Google mobility dataset by using the MTI dataset. The data sources of Google mobility report dataset are from Google accounts' location history on mobile devices. In order to check the representativeness of Google mobility dataset, we run a same model using the MTI dataset and Google dataset respectively. Both datasets have the metric of work trips. MTI dataset records the work trips per person while Google dataset records the standardized work place visits. We use the work trips as the outcome variable and run the DID and DDD models using these two datasets within the time window (2/15/2020–3/31/2020). Table I presents the estimation results. The results using different datasets are consistent. Both results show that stay-at-home order reduced overall work trips significantly while the effect on lower-income groups was much smaller compared to higher-income groups. Thus, we believe the Google mobility report dataset can also be representative.

Table I
The DID and DDD estimations using MTI and Google datasets.

	MTI data	MTI data	Google data	Google data
	Work trips per person	Work trips per person	Standardized work place visits	Standardized work place visits
	(1)	(2)	(3)	(4)
Stay-at-Home Order	−0.05***	−0.07***	−7.6***	−12.42***
	(0.002)	(0.004)	(0.23)	(0.46)
Stay-at-Home Order × Lower-Income		0.02***		5.89***
		(0.004)		(0.49)
Control variables:				
COVID-19 new cases	Yes	Yes	Yes	Yes
COVID-19 accumulative cases	Yes	Yes	Yes	Yes
Daily maximum temperature	Yes	Yes	Yes	Yes
Daily precipitation	Yes	Yes	Yes	Yes
Snow	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	110,606	110,606	104,301	104,301
R-square	0.33	0.33	0.79	0.79

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at county level, which are in parentheses. We use the data in time window (2/15/2020–3/31/2020) to fit these models. The outcome variable of work place visits is standardized by the Google mobility report, which is the percent change compared to the baseline in visits to work places. The baseline is the median value for the corresponding day of the week, during the 5- week period Jan 3–Feb 6 2020. "Yes" means the control variables and fixed effects indicated in the left column are included in the model.

Appendix P. Robustness check using census tract level data

To address the concern of "ecological fallacy", we conduct another robustness check by running the same DID (difference-in-differences) and DDD (difference-in-difference-in-differences) models using the SafeGraph dataset at the census tract level. There are 74,134 census tracts in the U.S., so the census tract is much smaller compared to the county and the variation within a census tract could also be much smaller compared to a county. We can observe the daily percentage of staying at home in each census tract based on the Safegraph dataset,[8] and observe the personal income per capita in 2019 based on the U.S. census dataset. The data sources of the Safegraph dataset are anonymous GPS pings of mobile devices, such as smart phone's apps using location services. The Safegraph dataset adopts an approach of post-hoc stratified re-weighting[9] to correct sampling bias and improve the representativeness.

Table J presents the estimations of DID and DDD models using the census tract level data. We use the data in time window 1 (01/01/2020–03/31/2020) to fit the models. In column (2), the lower income variable is defined by state average, which takes value one if a census tract's personal income per capita is less than the average personal income per capita of the state to which it belongs. In column (3), the lower income is defined by county average, which takes value one if a census tract's personal income per capita is less than the average personal income per capita of the county to which it belongs. The robustness check results are all consistent with our main results. The stay-at-home orders increased the percentage of staying at home and there are significant diverse effects between the lower- and upper- income groups.

Table J
The estimations of DID and DDD models using the census tract level data.

	Time window 1 (01/01/2020–03/31/2020)		
	Outcome: Percentage of staying at home		
	(1)	(2)	(3)
		Lower income defined by state average	Lower income defined by county average
Stay-at-Home Order	5.16***	9.30***	7.83***
	(0.05)	(0.07)	(0.07)
Stay-at-Home Order × Lower-Income		−7.10***	−4.87***
		(0.08)	(0.08)
Control variables:			
COVID-19 new cases	Yes	Yes	Yes
COVID-19 accumulative cases	Yes	Yes	Yes
Daily maximum temperature	Yes	Yes	Yes
Daily precipitation	Yes	Yes	Yes
Snow	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Census tract FE	Yes	Yes	Yes
Observations	6,089,923	6,089,923	6,089,923
R-square	0.4	0.41	0.4

[8] We obtain the national mobility data from SafeGraph: https://www.safegraph.com/covid-19-data-consortium

[9] Measuring and Correcting Sampling Bias in Safegraph Patterns for More Accurate Demographic Analysis, https://www.safegraph.com/blog/measuring-and-correcting-sampling-bias-for-accurate-demographic-analysis

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are clustered at census tract level, which are in parentheses. "Yes" means the control variables and fixed effects indicated in the left column are included in the model.

References

Abbott, J.K., Klaiber, H.A., 2011. An embarrassment of riches: confronting omitted variable bias and multi-scale capitalization in hedonic price models. Rev. Econ. Stat. 93 (4), 1331–1342.

Abouk, R., Heydari, B., 2020. The Immediate Effect of COVID-19 Policies on Social Distancing Behavior in the United States (SSRN Working Paper).

Adams-Prassl, A., Boneva, T., Golin, M., Rauh, C., 2020. The Large and Unequal Impact of COVID-19 on Workers. VoxEU.org. https://voxeu.org/article/large-and-unequal-impact-covid-19-workers.

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., Yang, D., 2020. Polarization and Public Health: Partisan Differences in Social Distancing during the Coronavirus Pandemic (No. w26946). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w26946.

Andersen, M., 2020. Early evidence on social distancing in response to COVID-19 in the United States. SSRN J. https://doi.org/10.2139/ssrn.3569368.

Anderson, R.M., Heesterbeek, H., Klinkenberg, D., Hollingsworth, T.D., 2020. How will country-based mitigation measures influence the course of the COVID-19 epidemic? Lancet 395, 931–934. https://doi.org/10.1016/S0140-6736(20)30567-5.

Angrist, J.D., Pischke, J.S., 2008. Mostly Harmless Econometrics: An empiricist's Companion. Princeton university press.

Atkeson, A., 2020. What Will Be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios (No. w26867). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w26867.

BEA, 2020. "Gross Domestic Product First Quarter of 2020 (Advance Estimate)." Technical Note. Washington D.C.: U.S. Bureau of Economic Analysis, April 29. https://www.bea.gov/system/files/2020-05/tech1q20_adv_0.pdf.

BLS, 2020. The Employment Situation – July 2020. Bureau of Labor Statistics, Department of Labor. Washington D.C. Department of Labor.

Brough, R., Freedman, M., Phillips, D.C., 2020. Understanding Socioeconomic Disparities in Travel Behavior during the Covid-19 Pandemic.

CERP, 2020. A Basic Demographic Profile of Workers in Frontline Industries. Center for Economic and Policy Research. https://cepr.net/a-basic-demographic-profile-of-workers-in-frontline-industries/ (accessed 6.21.20).

Chapman, T., 2020. How the COVID-19 Pandemic Exposes the Frailty of Social Protection in the US. Issue No.352. The Observer Research Foundation.

Chen, S., Yang, J., Yang, W., Wang, C., Bärnighausen, T., 2020. COVID-19 control in China during mass population movements at new year. Lancet 395, 764–766. https://doi.org/10.1016/S0140-6736(20)30421-9.

Coven, J., Gupta, A., 2020. Disparities in Mobility Responses to COVID-19 (NYU Stern Working Paper).

Cowling, B.J., Ali, S.T., Ng, T.W.Y., Tsang, T.K., Li, J.C.M., Fong, M.W., Liao, Q., Kwan, M.Y., Lee, S.L., Chiu, S.S., Wu, J.T., Wu, P., Leung, G.M., 2020. Impact assessment of non-pharmaceutical interventions against coronavirus disease 2019 and influenza in Hong Kong: an observational study. Lancet Public Health 5, e279–e288. https://doi.org/10.1016/S2468-2667(20)30090-6.

Davis, L.W., Wolfram, C., 2012. Deregulation, consolidation, and efficiency: Evidence from US nuclear power. Am. Econ. J. Appl. Econ. 4 (4), 194–225.

Davis, Lucas W., Fuchs, Alan, Gertler, Paul, November 1, 2014. Cash for Coolers: Evaluating a Large-Scale Appliance Replacement Program in Mexico. American Economic Journal: Economic Policy 6 (4), 207–238. https://doi.org/10.1257/pol.6.4.207.

Fang, H., Wang, L., Yang, Y., 2020. Human mobility restrictions and the spread of the novel coronavirus (2019-nCoV) in China (preprint). Health Econ. https://doi.org/10.1101/2020.03.24.20042424.

Fiscella, K., Williams, D.R., 2004. Health Disparities Based on Socioeconomic Inequities: Implications for Urban Health Care: Academic Medicine, 79, pp. 1139–1147. https://doi.org/10.1097/00001888-200412000-00004.

Fong, M.W., Gao, H., Wong, J.Y., Xiao, J., Shiu, E.Y.C., Ryu, S., Cowling, B.J., 2020. Nonpharmaceutical measures for pandemic influenza in nonhealthcare settings—social distancing measures. Emerg. Infect. Dis. 26, 976–984. https://doi.org/10.3201/eid2605.190995.

Furceri, D., Loungani, P., Ostry, J., Pizzuto, P., 2020. Will covid-19 affect inequality? Evidence from past pandemics. Covid Econ. 12 (138–57), 214.

Ghader, S., Zhao, J., Lee, M., Zhou, W., Zhao, G., Zhang, L., 2020. Observed mobility behavior data reveal social distancing inertia. arXiv published online Apr 30, 2020. https://arxiv.org/abs/2004.14748 (preprint).

Gilens, M., 2005. Inequality and democratic responsiveness. Public Opin. Q. 69, 778–796. https://doi.org/10.1093/poq/nfi058.

Glaeser, E.L., Kahn, M.E., Rappaport, J., 2008. Why do the poor live in cities? The role of public transportation. J. Urban Econ. 63, 1–24.

Goodreau, S.M., Pollock, E.D., Birnbaum, J.K., Hamilton, D.T., Morris, M., on behalf of the Statnet Development Team, 2020. Can't I Please Just Visit One Friend?: Visualizing Social Distancing Networks in the Era of COVID-19. http://statnet.org/COVID-JustOneFriend/.

Google, 2020. COVID-19 Community Mobility Report [WWW Document]. COVID-19 Community Mobility Report. https://www.google.com/covid19/mobility?hl=en (accessed 6.21.20).

Greenstone, M., Nigam, V., 2020. Does Social Distancing Matter? (SSRN Journal).

Harris, J., 2020. The Coronavirus Epidemic Curve is Already Flattening in New York City, NBER Working Paper No. 26917. National Bureau of Economic Research, Cambridge, MA.

Hausman, C., Rapson, D.S., 2018. Regression discontinuity in time: considerations for empirical applications. Ann. Rev. Resour. Econ. 10, 533–552.

Imbens, G.W., 2004. Nonparametric estimation of average treatment effects under exogeneity: a review. Rev. Econ. Stat. 86 (1), 4–29.

IMF, 2020a. World Economic Outlook 2020, Chapter 1 the Great Lockdown. International Monetary Fund, Washington D.C.

IMF, 2020b. World Economic Outlook Update, June 2020: A Crisis like no Other, An Uncertain Recovery. International Monetary Fund, Washington D.C.

Karner, A., Niemeier, D., 2013. Civil rights guidance and equity analysis methods for regional transportation plans: a critical review of literature and practice. J. Transp. Geogr. 33, 126–134. https://doi.org/10.1016/j.jtrangeo.2013.09.017.

Kissler, S.M., Tedijanto, C., Goldstein, E., Grad, Y.H., Lipsitch, M., 2020. Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. Science. https://doi.org/10.1126/science.abb5793 eabb5793.

Konisky, D.M., 2009. Inequities in enforcement? Environmental justice and government performance. J. Policy Anal. Manag. 28, 102–121. https://doi.org/10.1002/pam.20404.

Link, B.G., Phelan, J., 1995. Social conditions as fundamental causes of disease. J. Health Soc. Behav. 80–94. https://doi.org/10.2307/2626958.

Lucas, K., 2012. Transport and social exclusion: where are we now? Transp. Policy 20, 105–113. https://doi.org/10.1016/j.tranpol.2012.01.013.

Lunt, M., 2014. Propensity Anal. Stata Rev. 1 (1), 30.

Marshall, J.D., 2008. Environmental inequality: air pollution exposures in California's south coast Air Basin. Atmos. Environ. 42, 5499–5503. https://doi.org/10.1016/j.atmosenv.2008.02.005.

Maryland Transportation Institute, . University of Maryland COVID-19 Impact Analysis Platform. https://data.covid.umd.edu last accessed on [April 30, 2020]. University of Maryland, College Park, USA.

Mechanic, D., 2002. Disadvantage, inequality, and social policy. Health Aff. 21, 48–59. https://doi.org/10.1377/hlthaff.21.2.48.

Miller, C.C., Kliff, S., Sanger-Katz, M., 2020. Avoiding Coronavirus May be a Luxury some Workers Can't Afford (The New York Times).

Morello-Frosch, R., Pastor, M., Sadd, J., 2001. Environmental justice and Southern California's "Riskscape": the distribution of air toxics exposures and health risks among diverse communities. Urban Aff. Rev. 36, 551–578. https://doi.org/10.1177/10780870122184993.

Nayak, A., Islam, S.J., Mehta, A., Ko, Y.-A., Patel, S.A., Goyal, A., Sullivan, S., Lewis, T.T., Vaccarino, V., Morris, A.A., Quyyumi, A.A., 2020. Impact of social vulnerability on COVID-19 incidence and outcomes in the United States (preprint). Public Global Health. https://doi.org/10.1101/2020.04.10.20060962.

Nelson, B., 2020. Seattle's covid-19 lessons are yielding hope. BMJ. https://doi.org/10.1136/bmj.m1389 m1389.

New York City, 2020. New York City's Frontline Workers.

Painter, M., Qiu, T., 2020. Political beliefs affect compliance with COVID-19 social distancing orders. SSRN J. https://doi.org/10.2139/ssrn.3569098.

Pan, Y., Darzi, A., Kabiri, A., Zhao, G., Luo, W., Xiong, C., Zhang, L., 2020. Quantifying human mobility behavior changes in response to non-pharmaceutical interventions during the COVID-19 outbreak in the United States. arXiv published online May 4, 2020. http://arxiv.org/abs/2005.01224 (preprint).

Pereira, R.H.M., Schwanen, T., Banister, D., 2017. Distributive justice and equity in transportation. Transp. Rev. 37, 170–191. https://doi.org/10.1080/01441647.2016.1257660.

Prem, K., Liu, Y., Russell, T.W., Kucharski, A.J., Eggo, R.M., Davies, N., Jit, M., Klepac, P., Flasche, S., Clifford, S., Pearson, C.A.B., Munday, J.D., Abbott, S., Gibbs, H., Rosello, A., Quilty, B.J., Jombart, T., Sun, F., Diamond, C., Gimma, A., van Zandvoort, K., Funk, S., Jarvis, C.I., Edmunds, W.J., Bosse, N.I., Hellewell, J., 2020. The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: a modelling study. Lancet Public Health S2468266720300736. https://doi.org/10.1016/S2468-2667(20)30073-6.

Ruben, Ruerd, Pender, John, August 2004. Rural Diversity and Heterogeneity in Less-Favoured Areas: The Quest for Policy Targeting. Food Policy 29 (4), 303–320. https://doi.org/10.1016/j.foodpol.2004.07.004.

Sanchez, T.W., Wolf, J.F., 2005. Environmental Justice and Transportation Equity, p. 25.

Sanchez, T., Stolz, R., Ma, J., 2003. Moving to Equity: Addressing Inequitable Effects of Transportation Policies on Minorities. The Civil Rights Project at Harvard University, Cambridge, MA.

Sears, James, Villas-Boas, J.Miguel, Villas-Boas, Sofia, Villas-Boas, Vasco, 2020. Are We #StayingHome to Flatten the Curve? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3569791.

Smeeding, T.M., 2005. Public policy, economic inequality, and poverty: the United States in comparative perspective*. Soc. Sci. Q. 86, 955–983. https://doi.org/10.1111/j.0038-4941.2005.00331.x.

Soroka, Stuart N., Wlezien, Christopher, 2008. On the Limits to Inequality in Representation. PS: Political Science and Politics 41 (2), 319–327. https://www.jstor.org/stable/20452181.

State of Delaware, 2020. Essential and Non Essential Business Categories During Coronavirus Closure.

State of Vermont, 2020. State of Vermont Critical Business List.

Swagel, P., 2020. Updating CBO's Economic Forecast to Account for the Pandemic Congressional Budget Office.
Tomer, A., Kane, J., 2020. How to Protect Essential Workers during COVID-19. Brookings Institute, Washington D.C.
van Dorn, A., Cooney, R.E., Sabin, M.L., 2020. COVID-19 exacerbating inequalities in the US. Lancet 395, 1243–1244. https://doi.org/10.1016/S0140-6736(20)30893-X.
Zhang, L., Ghader, S., 2020. Data Analytics and Modeling Methods for Tracking and Predicting Origin-Destination Travel Trends Based on Mobile Device Data (Federal Highway Administration Exploratory Advanced Research Program).
Zhang, L., Ghader, S., Pack, M.L., Xiong, C., Darzi, A., Yang, M., Sun, Q., Kabiri, A., Hu, S., 2020. An interactive COVID-19 mobility impact and social distancing analysis platform. medRxiv. https://doi.org/10.1101/2020.04.29.20085472 published online May 5, 2020. (preprint).