Social distancing responses to COVID-19 emergency declarations strongly differentiated by income

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In the absence of a vaccine, social distancing measures are one of the primary tools to reduce the transmission of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) virus, which causes coronavirus disease 2019 (COVID-19). We show that social distancing following US state-level emergency declarations substantially varies by income. Using mobility measures derived from mobile device location pings, we find that wealthier areas decreased mobility significantly more than poorer areas, and this general pattern holds across income quantiles, data sources, and mobility measures. Using an event study design focusing on behavior subsequent to state emergency orders, we document a reversal in the ordering of social distancing by income: Wealthy areas went from most mobile before the pandemic to least mobile, while, for multiple measures, the poorest areas went from least mobile to most. Previous research has shown that lower income communities have higher levels of preexisting health conditions and lower access to healthcare. Combining this with our core finding—that lower income communities exhibit less social distancing—suggests a double burden of the COVID-19 pandemic with stark distributional implications.

inequalities | COVID-19 | social distancing

In response to the threat of coronavirus disease 2019 (COVID-19), national and local governments around the world have declared emergencies, promoted safer-at-home orders, and required business closures to increase social distancing and reduce the risk of transmission. While social distancing during the 2009 H1N1 swine flu pandemic was effective in reducing infections, indirect evidence from a single region suggested this response was most pronounced in higher socioeconomic level households (1). In this paper, we use anonymized location pings data from mobile devices covering the entire United States to provide direct evidence of systematic differences in social distancing behavior across income levels during the COVID-19 pandemic. We show that social distancing following state emergency declarations is substantial overall, but dramatically increases in intensity with income. This finding is consistent across social distancing metrics from three difference sources of mobile device data. There is an urgent need to identify whether and to what extent lower-income communities are systematically exposed to greater COVID-19 risk, especially if such effects are to be ameliorated before the full toll has accrued. Rapidly growing unemployment in a system of predominantly employer-based benefits—most critically, health insurance—adds to the urgency (2). More generally, lower-income communities already experience worse health outcomes (3) and have a lower capacity to cope with economic and health shocks. This implies a double burden of COVID-19: lower-income communities appear to be most vulnerable to the economic and health impacts of the disease [e.g., due to less access to healthcare (4) and preexisting health conditions (5)], and here we show that they also exhibit less of the social distancing that could buffer against it.

Unpacking the mechanisms through which income is associated with behavioral responses to social distancing policies is a long-run challenge. Mechanisms might involve differences in

components that drive choice under uncertainty: access to information, mapping of information into subjective probabilities of outcomes and risk preferences (6), and constraints affecting capacity or ability to respond. For example, studies highlight the existing intersection of income and unequal access to information (7), differences in political preferences that may influence how information is processed (8), and attitudes toward risk (9). Lower-income households are also directly constrained in many ways, for example, in the capacity to work from home, take paid or unpaid time off of work, and draw on savings to limit shopping trips to meet basic needs (10). Concentration of these households in denser residential areas may also complicate social distancing. With respect to environmental risk more broadly, environmental economists have emphasized the role of private defensive investments, whereby individuals invest in measures that reduce their exposure to environmental harms (e.g., air filters to reduce exposure to air pollution), and the extent to which such investments are limited by their income (11).

While the data and analysis in this brief report do not yet allow for disentangling the causal roles of these various drivers, as a first step in this long-run effort, we document stark income-based differences in the response to recent state-level COVID-19 emergency declarations in the United States.

Results

Fig. 1 shows the daily average of four mobility measures for weekdays in the United States from January 1 to April 21, 2020. These measures are averaged by income quintile at the smallest spatial unit available, either census tract (Fig. 1, *Left*) or county (Fig. 1, *Right*). Each panel shows a different daily mobility measure derived from mobile device location pings data: percentage of devices staying completely at home (Fig. 1, *Top Left*), device exposure given by the average number of devices at all of the locations visited by a device in a day (Fig. 1, *Top Right*), median distance traveled outside the home, computed by taking the median distance traveled among the devices that left their home (Fig. 1, *Bottom Left*), and percentage change in device presence at locations of retail and recreation relative to the 5-wk period from January 3 to February 6, 2020 (Fig. 1, *Bottom Right*).

All measures in Fig. 1 show an abrupt shift occurring in the month of March consistent with social distancing. They also show a clear pattern by income level: Distancing responses range systematically from weakest for the bottom income quintile to strongest for the top income quintile. Notably, for the "completely at home" variable, which we view as the most appealing
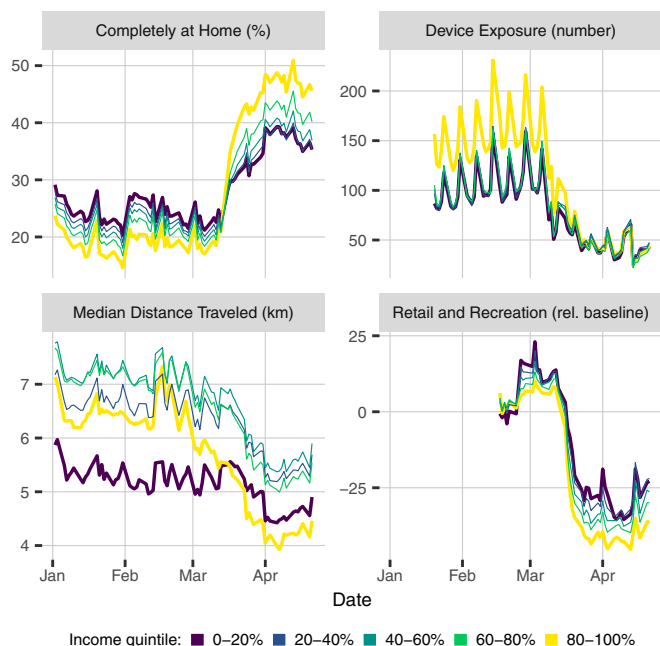
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Fig. 1. Daily mean mobility measures in the United States from mobile devices for weekdays from January 1 to April 21, 2020 by quintiles of median income at the census tract (*Left*) or county (*Right*) level. Thicker lines indicate the top and bottom quintile. Each panel shows a different measure of social distancing behavior. Data are from SafeGraph, PlaceIQ, and Google.

pare income-differentiated responses to the state declaration. Coefficient estimates for days preceding each state's declaration inform us about potential pretrends, that is, changes in behavior ahead of the policy announcement. In a classical event study analysis, substantial pretrends are a source of concern, for example, indicating prepolicy response.

Fig. 2 shows event study estimates of the change in the four separate mobility measures (each panel) relative to the state emergency declaration date. Estimates for each measure (panel) are differentiated by county income quantile (lines within each panel). We find that pretrends are absent from our preferred social distancing measure "completely at home" as well as "device exposure." In contrast, for "median distance traveled," we find that individuals in wealthier counties show substantial behavior change before their state's declaration, while "retail and recreation" shows an early pretrend that is then absent in the 2 wk before the event. Postevent, however, for the majority of measures, we estimate large and persistent social distancing behavior that is also strongly differentiated by income quintile. For example, for "completely home," relative to the postdeclaration average for all counties, the top income quintile response is essentially doubled, while the bottom income quintile response is halved. Substantially more social distancing for the top income quintile is also apparent for "device exposure" and "retail and recreation."

Explicitly identifying the relationship between social distancing and reductions in COVID-19 incidence is a key long-run research need. However, the likely presence of two-way feedback between distancing and disease will require a creative and comprehensive approach for responsible causal inference. While state emergency declarations were typically the first major steps taken in most jurisdictions, states also took subsequent measures, and thousands of counties and cities took steps at a finer spatial scale; a longer-run exhaustive accounting of the policy drivers of distancing should account for these.

Overall, we show that social distancing following states' emergency declarations is substantial and strongly differentiated by

measure of social distancing, the income differential is reversed after March: Individuals in the wealthiest census tracts shift from least to the most likely to completely stay at home, and vice versa for the poorest census tracts.
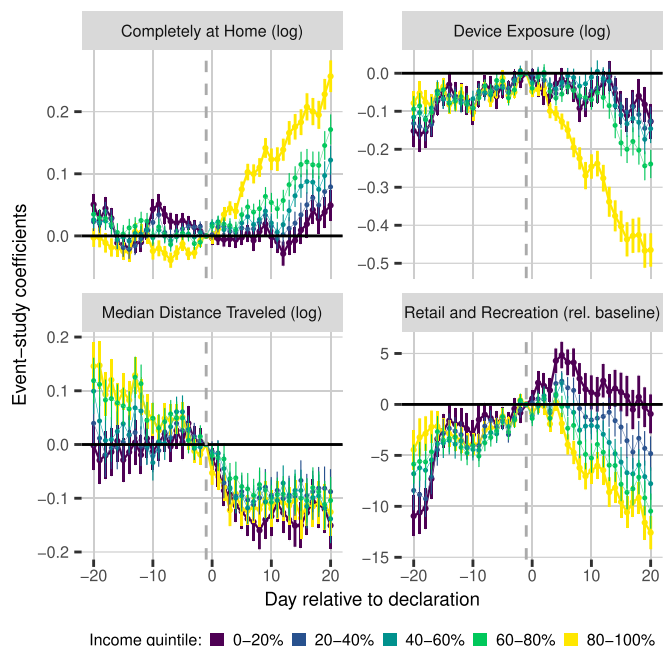
The "device exposure" measure provides a proxy capturing how often people are going to places combined with how crowded those places are. We found that the prepandemic income–mobility disparity—where high-income counties have substantially higher exposure—converges to parity under the pandemic. The "median distance traveled" income pattern diverges from the income-ranked relationship observed for other measures. This distance increases and then decreases as income quintile increases; that is, middle-income quintile travelers typically move farther in a day than the lowest and highest income quintile. This pattern holds before and after the arrival of the pandemic, with the highest income quintile again showing the biggest change in behavior consistent with social distancing. The time series discussed above suggest that income differences are key determinants of mobile devices-based mobility measures. However, poorer and wealthier census tracts (or counties) are located in areas with different characteristics, where measures inducing social distancing may have been mandated at different times. To address both concerns in a multivariate framework, we use a panel regression analysis with an event study design to estimate how social distancing behaviors are related to state emergency declarations, and how the response varies by income group (Eq. **1**). The event study model includes county fixed effect to control for the main effect of time-invariant county-specific factors such as income and population density, and also includes day fixed effects to control for temporal shocks common to all counties (e.g., federal policies). Furthermore, as is standard with event study designs, we estimate the dynamic impact of the mandates by including lags and leads of the event date (12). More specifically, we estimate a separate response for each of 20 days before and after an emergency declaration (normalized to occur at relative day 0), for each income quintile, allowing us to com-

Fig. 2. Event study estimates of the change in a mobility measure (each panel) relative to state emergency declarations, differentiated by median income quintile at the census tract (*Left*) or county (*Right*) level. Error bars represent 90% CIs. State declaration occurs at day $k = 0$.

county-level income. While these top-line results are consistent across distancing measures, other differences between them (e.g., income quantile convergence in "device exposure" but not in other measures) show the importance of considering multiple metrics. Our findings are in line with previous research showing an association between income and response to government prompts for disaster preparedness (13) as well as increased exposure of lower-income populations to environmental harms such as air pollution (14). The results highlight the urgent need for policy options to build capacity for social distancing—and other COVID-19 risk reduction measures—in lower-income regions.

Data Sources. We assembled a longitudinal dataset of daily mobility measures and state-level emergency declarations for January–April 2020 (15). Daily mobility measures based on anonymized and aggregated mobile device data were obtained from SafeGraph, Google, and Place IQ. SafeGraph data ("completely home" and "median distance traveled") are provided at the census block group level (period January 1 to April 21, 2020). PlaceIQ data were used by ref. 16 to derive the "device exposure" variable at the county level (period January 20 to April 21, 2020). Google Mobility data ("retail and recreation") are provided at the county level over the period February 15 to April 21, 2020 (expressed in changes relative to the 5-week period from January 3 to February 6, 2020). Of the three datasets, SafeGraph data provide the best spatial coverage, with almost all counties represented. Google Mobility data were not consistently available for all days and counties due to anonymity constraints. More detail on specific measures is provided in *Data Availability*. US states emergency declaration dates (date effective) were obtained from the National Association of Counties and updated with media reports. Finally, county and census tract median income quantiles were constructed using American Community Surveys (ACS) data (2014–2018, 5-year pooled).

Model. We estimated the impact of a state's emergency declaration on mobility outcome Y_{ct} using the event study framework in Eq. **1**, where Y_{cd} is the mobility measure in county c on calendar day d. We index income quintiles by $q \in Q$ with $Q = \{1, 2, \ldots, 5\}$, and index days relative to event by k. D_{ckq} is a dummy variable equal to 1 when county c belonging to income quintile q is k days away from being "treated" by the state declaration. Formally, $D_{ckq} = \mathbb{1}\{d - ED_c = k \cap q_c = q\}$, where ED_c is the state emergency declaration day for county c. As is usual with event studies, we also included a single dummy for all rela-

tive days before our event window (over 20 days predeclaration) denoted by $k = -21^-$, and another for all relative years after, $k = 21^+$ (over 20 days postdeclaration).

$$Y_{cd} = \sum_{k=-21^-}^{k=21^+} \sum_{q \in Q} \gamma_{kq} \cdot D_{ckq} + \boldsymbol{\theta} X_{cd} + \lambda_c + \lambda_d + \epsilon_{cd}. \quad \text{[1]}$$

The dummy for $k = -1$ is omitted to serve as baseline. We further add, as a time-varying control variable, the cumulative number of COVID-19 infected cases in each county (X_{cd}). County fixed effects (λ_c) control for unobserved static differences between counties, and day fixed effects (λ_d) control for national-level shocks. Finally, ϵ_{cd} is a county/day-specific error term. Standard errors are clustered at the county level.

Additional Robustness Checks. We ran similar specifications using five different mobility measures provided by SafeGraph ("full time work behavior," "part time work behavior," "median home share," "median home dwell time," and "delivery behavior") and the PlaceIQ "device exposure" variable, both in levels and in logs, as well as the Google Mobility variables ("retail and recreation," "grocery and pharmacy," and "workplaces"). Key results are consistent across all these alternative specifications. We alternatively included the cumulative number of known infected cases until the state declares an emergency, or excluded this variable altogether. This did not substantially affect our findings. We also conducted the analyses by income deciles instead of quintiles, which provided very similar results.

Data Availability. Mobility data are available from PlaceIQ via the "device exposure" variable derived by and available from ref. 16; Google Mobility Reports (available at https://www.google.com/covid19/mobility/); and SafeGraph (freely provided upon request submitted at https://www.safegraph.com/covid-19-data-consortium). ACS data are provided on the ACS website. State emergency declaration dates and code used to run the models are available on Github https://github.com/JoakimWeill/covid_mobility_income_PNAS.

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