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Socioeconomic restrictions slowdown COVID-19 far more effectively than favorable weather-evidence from the satellite

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HIGHLIGHTS

• The first global quantification of COVID-19 spread by socioeconomic activities (SA)
• Objective daily SA records in 213 polities proxied by satellite NO2 concentration.
• Most climate variables become statistically insignificant more developed countries.
• The trend map of spared infectees shows the risk of reopening the economy.
• The trend until mid-April suggests Africa and Latin America can become a hotspot.

GRAPHICAL ABSTRACT

ABSTRACT

We model the impact of restricting socioeconomic activities (SA) on the transmission of COVID-19 globally. Countries initiate public health measures to slow virus transmission, ranging from stringent quarantines including city lockdown to simpler social distancing recommendations. We use satellite readings of NO2, a pollutant emitted from socioeconomic activities, as a proxy for the level of social-economic restrictions, and discuss the implications under the influences of weather. We found that restricting SA has a leading contribution to lowering the reproductive number of COVID-19 by 18.3% ± 3.5%, while air temperature, the highest contributor among all weather-related variables only contributes 8.0% ± 2.6%. The reduction effects by restricting SA becomes more pronounced (23% ± 3.0%) when we limited the data to China and developed countries where the indoor climate is mostly controlled. We computed the spared infectees by restricting SA until mid-April. Among all polities, China spared 40,964 (95% CI 31,463-51,470) infectees with 37,727 (95% CI, 28,925-47,488) in the Hubei Province, the epicenter of the outbreak. Europe spared 174,494 (95% CI 139,202-210,841) infectees, and the United States (US) spared 180,336 (95% CI 142,860-219,445) with 79,813 (95% CI 62,887-97,653) in New York State. In the same period, many regions except for China, Australia, and South Korea see a steep upward trend of spared infectees due to restricting SA with the US and Europe far steeper, signaling a greater risk of reopening the economy too soon. Latin America and Africa show less reduction of transmissivity through the region-by-time fixed effects than other regions, indicating a higher chance of becoming an epicenter soon.

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1. Introduction

COVID-19 was declared a global pandemic by the World Health Organization (WHO) and has infected more than three million people by April 2020 (Dong et al., 2020). To date, it has a death rate 30–40 times death rate that of seasonal influenza (3–4% vs. 0.1%) and infects all ages (WHO, 2020). Managing a controlled transition from community transmission to a low-level is, at present, the best-case outcome in the short and medium-term in the absence of effective treatment and vaccine (WHO, 2020). Few countries impose stringent containment policies to slow the virus transmission, including city lockdown, and mandatory quarantine. Most other countries adopted milder public health measures, mainly to restrict socioeconomic activities (SA) such as shelter-in-place and recommendations of social distancing and self-quarantine. The degree to which SA is restricted varies dramatically with location, time, and climate regions and is difficult to measure directly, especially when citizen’s compliance with the governmental orders is in question. Consequently, the extent to which restricting SA helps suppress the COVID-19 is unknown, and questions arise whether huge sacrifices, including closing economy, are exerted in vain (4), especially if favorable weather conditions slow down the virus transmission as has been suggested by many news outlets. This study aims to examine how SA reduces the transmission of COVID-19 at global scale. SA is not intended as a substitute to the stringent policies such as city lockdown and mandatory quarantine but rather complementary to idiosyncratic public control methods and medical capacity. More importantly, it objectively reflects the public compliance to these policies.

Most previous studies on nonpharmaceutical COVID-19 mitigation rely on government announcements (Anderson et al., 2020; Dehning et al., 2020; Flaxman et al., 2020), travel records (Lai et al., 2020; Qiu et al., 2020), and epidemic parameters to predict the number of infectees in a single city, country, or regime (Grassly and Fraser, 2008; Lai et al., 2020; Prem et al., 2020; Qiu et al., 2020; Yang et al., 2020) in a future or counterfactual scenario if restrictions are lifted utilizing the susceptible-exposed-infectious removed (SEIR) modeling framework (Painter and Qiu, 2020). However, the quantification of the impact of SA restriction on COVID-19 spread, a mitigation measure that existed all over the world, is missing. Furthermore, these methods are hard, if at all possible to be applied globally because 1) neither global travel records nor global epidemic parameters are available, 2) divergence may occur between the policy announcement, practical implementation and public compliance (Briscese et al., 2020; Haffajee and Mello, 2020) and 3) validating the model only by the records from a stringently controlled region or country (e.g. Wuhan or China) might bias the estimation of an extreme scenario with no controls.

As a proxy for SA, we use satellite observations of the concentration of nitrogen dioxide (NO$_2$) at daily scale (Eskes et al., 2019) and build a panel regression model to quantify the impact of SA and weather conditions to the transmissibility of COVID-19 globally. We focus on the period of community spread because NO$_2$ concentration is significantly positively associated with SA (Castellanos and Boersma, 2012; Luo et al., 2014). We utilize the region-by-time fixed effects of the panel regression model to account for the unobservable time-varying regional factors (RTFE), including regional medical facility capacity, any additive control measures to SA restrictions, and natural time effects of virus transmissivity.

We use the effective reproductive number, $R_0$, to represent the daily dynamics of the transmissibility of COVID-19. $R_0$ is an indicator of the transmissibility of a virus, representing the average number of secondary infectees generated by a primary infectee (Van den Driessche and Watmough, 2008). For $R_0 > 1$, the number infected is likely to multiply, and for $R_0 < 1$, the virus is expected to die out. We compute $R_0$ using a widely adopted statistical approach (Flaxman et al., 2020; Lauer et al., 2020) that requires only the daily confirmed number of infectees, a globally available epidemic record.

2. Materials and methods

2.1. The reproductive number estimation

Since except for the number of infectees and deaths, epidemic parameters of COVID-19 are not globally available, we employ a stochastic approach (Flaxman et al., 2020) to estimate the reproductive number, $R_0$. The approach models the time delay from a person get infected and his/her clinical confirmation as a discrete stochastic number of days, and model the time between a person get infected and infect another person as another discrete stochastic number of days. Then $R_0$ of a given country or state/province at day $t$, $R_{0t}$, can be estimated from the daily confirmed number of infectees ($C$), via an intermediate variable, daily number of new infectors ($I_t$). The conversion from $C_t$ to $I_t$ is given by Eq. (1).

$$ I_t = \sum_{\tau=t-1}^{t-4} C_{\tau} \log_{2} \tau $$

where $C_{\tau}$ is the probability of an infectee to get clinical confirmation $\tau$ days since being infected (Lauer et al., 2020). Note that in Eq. (1), to estimate the $I$ on a given day, $C$ records with a 14-day extension need to be used. Therefore, we use the COVID-19 records until May 1 to study the period up to April 17, 2020. The conversion from $I_t$ to $R_{0t}$ is given by Eq. (2).

$$ R_{0t} = \frac{I_t}{\sum_{\tau=t-N}^{t-1} I_{\tau} g_{t-\tau}} $$

where $g_{\tau}$ is the probability of an infector to infect other people after $\tau$ days since being infected.

2.2. Record trimming for the noncommunity spread period

Non-local community spread can occur in three situations in a given response unit: 1) before the community spread, 2) a large number of infectors are imported after the end of community spread when the epidemic is under control. All three situations could result in an erroneous $R_0$ value significantly larger than the reality. For the first case, we simply set 30 accumulated cases as the minimum threshold for a community spread to start. For the second case, we identify a sharp peak of daily confirmed infectees. If the number of newly confirmed infectees on a single day is at least ten times of any other day within a 14-day window, it contains a significant number of imported cases. We, therefore, remove the 14-day window of the sample before the peak day from the panel regression. For the last case, if the newly confirmed infectees on four days in a fourteen-day window are zero after the beginning community spread, the community spread is considered as ended. Sample after the community spread will not be used. We also remove any response unit with shorter than ten days after community spread.

2.3. Data source and preprocessing

$R_0$ is estimated from daily clinical confirmation of COVID-19 infectees assembled at Johns Hopkins University in excel tables (Dong et al., 2020). The NO$_2$ concentration is retrieved from Sentinel-5P level 2 product (Eskes et al., 2019) at daily intervals of 3.5 km × 7.5 km nadir resolution in netcdf4 format. Climate predictors are extracted from the ERA 5 atmospheric reanalyses (ERA5, 2017) at hourly intervals and 0.25° × 0.25° grids in GRIB format. All climate predictors are averaged to daily mean and then averaged to the country or state/province weighted by population density from Gridded Population of the World.
2.4. The attribute model and software

We fit a panel regression model with region-by-time fixed effects (RTFE) (Correia, 2016; Greene, 2003) to quantify the contribution of SA and weather conditions to the response unit and region. A response unit is either a country or a province/state, depending on the availability of COVID-19 records. For example, records are available in China, the US, Canada, and Australia at the province/state level while only available at the country level in most other regions. \( r \) stands for the days after community spread (\( C_r > 30 \)). The world is divided into ten regions based on geographic proximity and data availability. They are China, the US, Europe, Africa, Latin America, Australia (Australia and New Zealand), West Asia, South Asia, East Asia, and Arctic (Canada and Russia). The contribution of each dependent variable can be then estimated by the product of the dependent-variable coefficient and value range over the response-variable value range (Tables S1–S4 in Appendix).

The reduction of \( R_0 \) by restricting SA can be estimated by the product of \( \beta_S \) and the difference between the log \( \text{NO}_2 \) under and the \( \text{NO}_2 \) restriction during the community spread of the last year. Note that we only averaged the same period using the year of 2019 because Sentinel-5P data is only available after June 2018. Substituting the hypothetical \( R_0, r \) back to Eq. (2), we can estimate the number of infectees with no restricted SA.

### 3. Results

Using worldwide records of 3,315,748 confirmed cases in 213 countries or polities (provinces/states, depending on the record availability) from late January to mid-April (1), we include in our sample if community spread dominates on that day and obtain 6386 daily \( R_0 \). Among commonly used weather variables (see Table S5 in Appendix), we find that SA, UV, temperature (\( T \)), wind speed (\( u \)), and relative humidity (RH) can well explain the daily \( R_0 \) dynamics (\( R^2 = 0.51 \) and all \( p < 0.001 \), Table S1 in Appendix). Table 1(a) shows a strong positive contribution of SA, moderately positive and negative contribution of temperature and UV, and weakly negative contribution of windspeed and RH to \( R_0 \). Therefore, SA restriction, UV illumination, high wind, and high humidity could reduce the transmission. SA has the highest contribution of 18.3% ± 2.0% (95% Confidence Interval, CI).

We further limit the study regions to China and developed countries to confirm the contribution of SA and weather. The \( R^2 \) is increased to 0.61, and the SA contribution is increased to 23.2% ± 3.0% (95% CI), 4.9% higher than the global scale, whereas UV, wind, and RH become insignificant (Table S2 in Appendix). The result might be explained by the fact that in more developed areas, people tend to stay indoors with a controlled climate most of the time (Morikawa et al., 2020). This suggests that simply relying on favorable weather conditions, such as warm weather and high UV that clearly have negative impacts on the spread, has strong limitations in stopping the virus transmission in these areas.

#### 3.1. The nonmonotonic temperature contribution

We suspect a nonmonotonic contribution of temperature by restricting temperature to low or high (\( T < 25 \degree C \) or \( T \geq 25 \degree C \)) in the regression because the coefficient of temperature changes from weakly positive to strongly negative (Table S3 vs. Table S4 in Appendix). We hypothesize that the virus might have a viable temperature range. This finding agrees with previous studies on coronavirus (Chan et al., 2011) and COVID-19 (Ficetola and Rubolini, 2020; Wang M. et al. 2020), but disagrees with most studies claiming temperature has a decreasing (Wang J. et al. 2020), increasing (Ma et al., 2020) or no effect (Yao et al., 2020) on the transmissibility. However, we note that the sample size, with only 747 samples, is relatively small when restricting temperature to high (\( T > 25 \degree C \)). More data in the incoming season are needed to confirm the temperature effects because most regions in the globe have not experienced a COVID-19 pandemic with high temperature.

#### 3.2. Global transmissibility reduction through restricting SA

We estimate the global decrease of \( R_0 \) due to the SA restriction of which the half-monthly mean is shown by Fig. 1. Because China had the earliest outbreak in late January, we estimate the \( R_0 \) reduction from late January to February only in China in Fig. 1(a)–(c) and the \( R_0 \) reduction globally from March to mid-April in Fig. 1(d)–(f). China imposed the most robust SA restriction policy at an early stage, from February through mid-March, and saw the largest reduction of \( R_0 \). The provinces with major outbreaks in China had an \( R_0 \) reduction from 0.08 to 0.18 in the first half of February and 0.02–0.12 in the latter half of February and the first half of March. China gradually lifted the restriction of SA in late March (Fig. 1(e) and (f)). In Europe, the \( R_0 \) reduction was 0.02–0.06 in late March and 0.0–0.06 in early April. The western US started SA restrictions in the latter half of March, earlier than the rest of the US. The western US saw a collective reduction of \( R_0 \) from 0.02 to 0.08 from later March to April while the eastern US started a collective \( R_0 \) reduction half a month later (early April).

Consequently, compared to a hypothetical scenario with no SA restriction during the community spread, we estimate in Fig. 2 that China spared 40,964 (95% CI 31,463–51,470) infectees with 37,727 (95% CI, 28,925–47,488) in the Hubei Province, the epicenter of the outbreak. Europe spared 174,494 (95% CI 139,202–210,841) infectees, where Germany, France, Spain, Italy, and United Kingdom spared 22,674 (95% CI 18,076–27,461), 24,463 (95% CI 19,527–29,541), 28,857 (95% CI 23,058–34,812), 32,541 (95% CI 25,855–39,479), 18,580 (95% CI 14,864–22,386) respectively. The United States (US) spared 180,336 (95% CI 142,860–219,445) with 79,813 (95% CI 62,887–97,653) in New York State (The full table of spared infectees over time is available in the Extended Databases in Appendix).

### Table 1

| Predictors | Contribution with 95% CI |
|------------|------------------------|
| (a)        |                        |
| SA         | 18.3 ± 3.5%            |
| Temperature| 8.0 ± 2.6%             |
| UV         | −7.9 ± 3.3%            |
| Windspeed  | −5.7 ± 1.8%            |
| RH         | 3.6% ± 1.9%            |
| (b)        |                        |
| SA         | 23.2 ± 3.0%            |
| Temperature| 5.6 ± 2.3%             |
| (c)        |                        |
| SA         | 21.4 ± 3.0%            |
| Temperature| 5.4 ± 2.0%             |
The number of spared infectees is a compound result of $R_0$ reduction and timing. Although the $R_0$ reduction in Europe and the US is significantly smaller than that in China, it spared significantly more infectees because of their higher number of infectors when the restriction of SA started. Fig. 3 shows the regional spared infectees through SA restrictions in half-month intervals. Only China Mainland, Taiwan, South Korea, and Australia show a diminished trend, as a result of the early restrictions of SA. In contrast, Europe and the US continue to see a large number of spared infectees growing exponentially by the end of this analysis. The rest of the world, though having a fewer number of spared infectees than Europe and the US, shows rapid growth.

3.3. Interpretation of the region-by-time fixed effects component

Fig. 4 shows the RTFE decreases fastest in Australia and China, indicating that $R_0$ was lowered by around 1–1.5 at the end of the analyses. We propose that Australia (including New Zealand) and China have the most prominent regional attributes to curve the transmissivity of the COVID-19 over time. These are the effective control policies additional to SA restriction, corresponding to Australia’s early adoption of mandatory quarantine of overseas arrivals and travel bans overseas (IMF, 2020) and China’s prompt increase of medical facilities including temporary hospitals, reinforced medical crews from other provinces to the outbreak center (Chan, n.d.), and stringent policies such as the lockdown of Wuhan city and mandatory quarantine of returning migrant (domestic) workers (IMF, 2020). The RTFE of Europe, US, and arctic countries started from a high value (1.2–1.5), though decreased rapidly, and has not yet enabled the reduction of $R_0$ as large as that of China and Australia at the end of our analyses (below or close to zero). This may indicate that their regional attributes, such as medical facility capacity, help with reducing COVID-19 transmissivity but are not yet as successful due to a large number of accumulative infectors. The RTFE of Africa and Latin America, though started with a low number (~0.5), does not show as much decrease as other regions over time. This suggests that the regional attributes, such as medical capacity and additional intervention policies, do not help much to curve the virus transmissivity. This finding raises serious pandemic concerns over Africa and Latin America.

4. Discussion

We present a panel regression approach to assess the impacts of SA restrictions and weather conditions on the transmissivity of COVID-19
at global scale using daily satellite NO₂ concentration. We further estimate the transmissivity reduction through the global efforts of restricting SA in terms of the reduced reproductive number and the number of spared infectees. SA restrictions clearly show significantly more impact than the weather. The impact of weather can be explained by the facts that 1) sunlight kills the virus before it can be transmitted, increases cell cytotoxicity and modulates the biosynthesis of vitamin D which are essential to promote immune responses (Moriyama et al., 2020); 2) higher relative humidity prevents viral particles traveling as far as it could in drier air (Ma et al., 2020); and 3) wind blows off virus concentration in the air. Although we suspect that the virus has a viable temperature range, as the previous coronavirus, we need more data in coming seasons to confirm the hypothesis since the globe has not experienced a full cycle of seasons with COVID-19. Different regions started to restrict SA at different stages after community spread and implemented them at different magnitudes, resulting in various situations at the end of these analyses. Specifically, China, South Korea, and Australia show diminished trends of the spared number of infectees, suggesting the pandemic might be under control there. The rest of the world show increasing trends, indicating a great risk of reopening economies too soon. Additionally, the RTFE of Africa and Latin America did not bring down \( R_0 \) as fast as the rest of the world, raising concerns about the pandemic development there.

Fig. 2. The spared infectees until mid-April due to restricting socioeconomic activities (SA). Administrative units with insufficient COVID-19 records during community spread cannot be estimated (marked as no data).

Fig. 3. Regional reduced populations from infection through limiting socioeconomic activities (SA). (95% CI shaded area).

Fig. 4. The contribution of region-by-time fixed effects (RTFE) to the \( R_0 \).
Our study has the following limitations. First, our panel regression model is built for attribution instead of prediction. Without a mechanism modeling to separately parameterize the impact of medical factors, additional control policies to SA restriction, it cannot estimate the number of spared infectees if all nonpharmaceutical policies were lifted, which could be up to many folds of the existing infectees (Lai et al., 2020). Second, since no transportation records are available at global scale, our attribution model cannot characterize the contribution by imported infectees. Lastly, $R_0$ is estimated from confirmed infectee records, which can be inaccurate due to the lack of tested cases, especially at the beginning of the outbreak and in regions with less testing capacity. Without globally distributed epidemic parameters of COVID-19 other than the available records, the adopted statistical estimation seems to be the only practical global solution.

CRediT authorship contribution statement

Xinxi Shen: Methodology, Investigation, Formal analysis, Writing - original draft. Chenkai Cai: Methodology, Investigation, Formal analysis, Writing - original draft. Hui Li: Conceptualization, Investigation, Writing - review & editing.

Declaration of competing interest

Authors declare no competing interests. Acknowledgments

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Data and materials availability

Data (1) are available online, Data (18) and (35) are available through the Copernicus Open Hub and Copernicus Climate Change Service (C3S) Climate Data Store respectively. The result table, code of pre-processing and panel regression is available at GitHub. Working paper. http://scorreia.com/research/hdfe.pdf.

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