No Place Like Home: A Cross-National Assessment of the Efficacy of Social Distancing during the COVID-19 Pandemic

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Submitted to: JMIR Public Health and Surveillance
on: May 04, 2020

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Abstract

Background: In the absence of a cure in the time of pandemics, social distancing measures seem to be the most effective intervention to slow down the spread of disease. Various simulation-based studies have been conducted in the past to investigate the effectiveness of such measures. While those studies unanimously confirm the mitigating effect of social distancing on the disease spread, the reported effectiveness varies from 10% to more than 90% reduction in the number of infections. This level of uncertainty is mostly due to the complex dynamics of epidemics and their time-variant parameters. A real transactional data, however, can reduce the uncertainty and provide a less noisy picture of social distancing effectiveness.

Objective: In this paper, we integrate multiple transactional data sets (GPS mobility data from Google and Apple as well as disease statistics data from ECDC) to study the role of social distancing policies in 26 countries wherein the transmission rate of the COVID-19 pandemic is analyzed over a course of five weeks.

Methods: Relying on the SIR model and official COVID-19 reports we first calculated weekly transmission rate (?) of the coronavirus disease in 26 countries for five consecutive weeks. Then we integrated that with the Google's and Apple's mobility data sets for the same time frame and used a machine learning approach to investigate the relationship between mobility factors and ? values.

Results: Gradient Boosted Trees (GBT) regression analysis showed that changes in mobility patterns, resulted from social distancing policies, explain around 47% of variation in the disease transmission rate.

Conclusions: Consistent with simulation-based studies, real cross-national transactional data confirms the effectiveness of social distancing interventions in slowing down spread of the disease. Apart from providing a less noisy and more generalizable support for the whole social distancing idea, we provide specific insights for public health policy makers as to what locations should be given a higher priority for enforcing social distancing measures. Clinical Trial: N/A

(JMIR Preprints 04/05/2020:19862)
DOI: https://doi.org/10.2196/preprints.19862

Preprint Settings

Original Manuscript

Original Paper

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Method: Relying on the SIR model and official COVID-19 reports, we first calculated the weekly transmission rate (β) of the coronavirus disease in 26 countries for five consecutive weeks. Then we integrated that with the Google's and Apple's mobility data sets for the same time frame and used a machine learning approach to investigate the relationship between mobility factors and β values.

Results: Gradient Boosted Trees (GBT) regression analysis showed that changes in mobility patterns, resulted from social distancing policies, explain around 47% of the variation in the disease transmission rate.

Conclusion: Consistent with simulation-based studies, real cross-national transactional data confirms the effectiveness of social distancing interventions in slowing down the spread of the disease. Apart from providing less noisy and more generalizable support for the whole social distancing idea, we provide specific insights for public health policy-makers as to what locations should be given a higher priority for enforcing social distancing measures.

Keywords: COVID-19, public health, social distancing, machine learning, pandemic

Introduction

As of mid-May 2020, around 4.5 million people around the globe have been infected by the new deadly coronavirus disease (COVID-19)[1]. In the absence of a vaccine or any other effective medications, public health experts and epidemiologists suggest *social distancing* as the most effective intervention to control the spread of the disease, a.k.a. "*flattening the curve*" [2,3]. Based on this notion, some serious restrictive policies (e.g., shutting down businesses and closure of schools) have been placed by the governments of the affected countries to encourage (and in some countries to force) people to *stay at home.*

The effectiveness of social distancing in response to an epidemic has been widely studied, mostly using simulation-based methods. Reluga[4], for instance, using a differential game approach, argues that optimal social distancing is only able to reduce the chance of infection by less than 30%. In another agent-based simulation study using a small population, Kelso et al. [5] show that depending on the epidemic's initial reproduction rate (R_0) and the delay since the first case until introduction of social distancing measures the disease's attack rate may be reduced between 10% to 73%. Ahmed et al. [6], in a systematic review of prior research works, discuss that social distancing measures in workplaces caused a median reduction of 23% in the cumulative H1N1 influenza attack rate during the 2009 pandemic. Earn et al. [7], in another study, have shown that school closure had a considerable mitigating effect on the incidence of pandemic influenza in Alberta, Canada. Also, multiple studies have discussed the effects of social distancing on the 1918 influenza pandemic [8–10].

With respect to the COVID-19 pandemic, specifically, some recent studies have discussed the effects, challenges, and consequences of social distancing policies. Andersen [11], for instance, shows that mandatory social distancing measures have been effective at reducing people's visits to public locations. Also, Kissler et al. [12] maintain that while social distancing is effective, it should be intermittently until 2022 to be able to fully control the epidemic. Similarly, Singh and Adhikari [13] discuss that a 3-week lockdown is insufficient for controlling the disease in India, and intermittent social distancing must be in place. In a simulation-based study, Koo et al. [14] have shown that under different scenarios for COVID-19's reproduction number (R_0: 1.5, 2, or 2.5) and social distancing interventions (combinations of quarantine, school closure, and distance working), number of infections may be reduced between 78.2% to 99.3%. Another simulation study in Australia shows that infected case isolation is the most effective social distancing intervention, among others (i.e., school closure, distance working, and community contact reduction) [15]. Using an online questionnaire approach, Luo et al. [16] showed that social distancing policies were effective in containing the spread of COVID-19 from Wuhan City to other areas of China. Greenstone and

Nigam [17] have estimated that social distancing measures in the US would save 1.7 million lives by October 2020, and the monetary mortality benefit involved in that is around $8 trillion.

Recently, particularly since the spread of COVID-19, some researchers have begun to utilize geolocation data obtained from navigation and tracking information systems to analyze the consequences of social distancing policies. Engle et al. [18], for example, using GPS data, have shown that a higher perceived prevalence of the disease in a small US community (from 0% to 0.003%) has caused mobility to reduce by 2.31%. Also, Queiroz et al. [19] use cell phone navigation data of millions of people in Sao Paulo to show that mandatory social distancing measures have effectively changed mobility patterns of people in the largest city of Brazil. A similar study is done by Warren and Skillman [20] to study mobility changes in the United States in response to COVID-19. In another study, Gibson and Rush[21] used data from a geographic information system to discuss the feasibility of implementing social distancing in informal settlements in Cape Town.

Simulation-based studies have consistently shown the overall mitigating role of various social distancing interventions on the spread of epidemics. However, due to the complexity and time-variant nature of diseases, the reported effectiveness of interventions in such studies varies a lot and, in most cases are relied on local assumptions; hence does not produce generalizable results.

Recently Google[22] and Apple[23] incorporations published data sets indicating changes in people's mobility (compared to an average baseline before the COVID-19 pandemic) in different categories of places (e.g., transit stations, grocery stores, etc.) and different types of activities (e.g., driving and walking) based on the GPS data collected from users of their navigation applications all around the world. Although these reports confirm the effectiveness of governments' incentive and restrictive policies to make people stay at home by indicating considerable decreases in mobility within public places (and in turn increase in mobility within residential areas), yet their effectiveness on slowing down the disease spread is not apparent. Particularly, since many countries are still experiencing increasing numbers of confirmed COVID-19 cases, in spite of having social distancing policies in effect for several weeks, the question is to what extent, if any, the changes in mobility patterns resulted from these policies were effective in managing the disease spread. The present study seeks to clarify this issue.

To this end, we rely on the SIR[1] model, one of the most common compartmental models in studying epidemics, along with official reports on the number of COVID-19 cases in different countries to estimate the average transmission rate of the disease (called β). While the original SIR model considers a time-invariant β value, intuitively, the speed of the epidemic can at least partially be

[1] Abbreviation for Susceptible-Infected-Recovered

manipulated over time, rendering the magnitude of parameter β to be time-variant (Katriel and Stone, 2012; Liu et al., 2020). Therefore, each estimation pertaining to a different time section (weeks, in our study) may potentially yield a different β value. In our study, these varying β values corresponding to the weekly mobility statistics with a seven-day lag (considered for the effect of mobility changes to be reflected on disease transmission rate). The resulted data set was used to train a machine learning regression algorithm for the relationship between mobility and disease transmission to be investigated. To the best of our knowledge, this is the first study that uses real transactional data to investigate the actual contribution of social distancing policies (through mobility reduction) in controlling the spread of a pandemic.

Method and data

Data

Google Inc. and Apple Inc. mobility datasets:

In April 2020, Google[22] and Apple[23] started sharing daily mobility data on select regions and select countries in the world. Google dataset incorporates five different mobility trend variables: Grocery and Pharmacy (places like supermarkets, farmers markets, drug stores, and pharmacies), Parks (national/local parks, public beaches, and gardens), Transit stations (public transport hubs including train, bus or subway stations), Retail and recreation (places like restaurants, cafes, shopping centers, movie theaters), Residential (places of residences), and Workplaces. The dataset show trends starting prior to the outbreak (Google does not provide any specific benchmark date) onwards. Apple dataset also shows the relative volume of directions requests also compared to a specific baseline volume of January 13, 2020. Google and/or Apple does not include mobility data on some of the countries among the top 30 (in terms of cumulative cases of COVID-19) such as Russia, China, the United Kingdom, Iran, and Algeria. Therefore, our analysis is limited to the countries both included in ECDC and mobility datasets.

While controlling COVID-19, many governments declare mandatory or optional quarantines or employ other policies. For simplicity, we used a 7-day window and transformed our daily mobility data into weekly. We also performed missing value imputation using linear interpolation during this transformation. Our mobility data started on 2/28/2020 and ended on 4/17/2020, covering a total of 7 weeks in 26 countries ($7 \times 26 = 182$ rows). For each country, using consecutive day pairs, we estimated mobility averages of 9 variables (See Table 1).

Table 1-The mobility data from the companies Apple Inc. and Google Inc.

	Starting Date	Ending Date	#Countries	# SubRegions

Google	2/15/2020	4/11/2020	131	1710		
Apple	1/13/2020	4/21/2020	63	89		
	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6
Google	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Apple	Driving	Walking	Transit			

ECDC COVID-19 data

In this study, our aim is to understand the relationships between reported mobilities and the dynamics of the COVID-19 outbreak. Several agencies offer up-to-date data aggregations of the number of cases, as well as the number of deaths from over 150+ countries, including the European Union, WHO, and Johns Hopkins. As one source of data, we used the European Centre for Disease Prevention and Control (ECDC) data updated daily on their website[24]. The data coverage is limited (no gender, or age breakdowns, no data on the number of recovered patients, or the number of tests conducted). We limit our analysis to the top 30 countries (in terms of the number of cumulative cases). After data transformations (see section 3.2), we trimmed our data according to the starting and ending dates in Error: Reference source not found.

Other datasets

During our study, in order to overcome the limitations of ECDC COVID-19 dataset (or similar dataset providers) we also make use of several other datasets provided by individual countries such as the US (covidtracking.com website by the Atlantic), Belgium (ECDC website), and Turkey (National Ministry of Health of Turkey). Such datasets include the number of recovered patients on a daily basis and are available as per search online.

Method

In order to understand the relationships between limited mobility and COVID-19's spread, we first set out to find a target variable depicting the speed of the spread of the virus. Using variables such as "number of daily cases" or "number of daily fatalities" is driven by many forces such as "natural course of the spread of the virus" and "limited mobility and other controllable effects." As we are interested in measuring the actual change in the diffusion of the spread, we decided to employ one of the most frequently used endemic models, the SIR. Instead of looking at the case and fatalities data, we investigate the relationship between the parameter changes of the SIR model and changes in the mobility dataset.

SIR model

Pandemics are first characterized by a number referred to as reproduction number, R_0. The number "roughly" indicates the expected number of new infections caused by a single infection; hence it has no unit. This is especially important during the early days of the infection's spread. While R_0 <1 implies no epidemic, greater R_0 may indicate a pandemic of a larger scale. For instance, while seasonal flu has R_0 of 1.3 [25], R_0 for COVID-19 is speculated to be around 2.2 [26,27]. During an outbreak, the trajectory of the number of infected over time follows a nearly bell-shaped curve. Depending on the severity of the infection, health care systems are concerned with the peak of this curve in order to provide adequate health care services. The number R_0 is simply obtained by multiplying "transmissibility per contact," "contacts per time unit," and "the recovery rate."

$$R_0 = \underbrace{\frac{infection}{contact} \times \frac{contact}{time}}_{\beta} \times \underbrace{\frac{time}{infection}}_{1/\gamma} \quad (1)$$

Perhaps the most frequently used model in epidemic models is the *SIR* model. The model categorizes individuals into three different compartments: susceptible (*S*), infected (*I*), and recovered (*R*)(hence, called compartmental models). Within the SIR model, the term β, the effective contact rate, controls the transition from compartment *S* to compartment *I*. This rate, measuring the number of new infections over time, maybe influenced through interventions such as social distancing, wearing protective gear, or handwashing. The term γ, on the other hand, refers to the effective recovery rate. Therefore, a shorter average infectious period ($1/\gamma$¿ translates into a larger γ recovery rate. γ is strongly linked to the duration of the disease, rather than policy changes. Within the *SIR* compartment model, this value controls the move from the compartment *I* to compartment *R*. The rates corresponding to inter-compartment transitions can be written as a set of differential equations as in (2-4) [28].

$$dS/dt = -\beta SI/N \quad (2)$$

$$dI/dt = \beta SI/N - \gamma I \quad (3)$$

$$dR/dt = \gamma I \quad (4)$$

While the set of differential equations is self-explanatory, the parameter estimations, especially at the beginning of an outbreak, are usually not quite straightforward. At the beginning of an outbreak, everyone may be considered as susceptible ($S \approx N$), and R_0 becomes β/γ. However, at later stages, R_0 determines the size of the compartment "*S*" ($S \neq N$); it becomes numerically more challenging to calculate an estimate.

Calculating γ

In order to determine a good approximation to the rate of recovery, we set out to estimate the average number of days from the case reported to recovery. We use reported data available from three different countries: Turkey, Belgium, and the US. By using a sliding window to investigate the correlation between the number of recovered and the number of new cases using a lag variable, we estimate the slide amount that maximizes the correlation between these two sets of numbers. While the results may depend on individual practices of the countries, our analysis consistently yielded the lag time to be 7 to 8 days regardless of the country (see the supplemental materials for more details). We, therefore, chose to set γ at $1/7.5=0.133$.

Aggregating reported case numbers for analysis

ECDC reports the number of daily cases. Cases do represent infection; however, the number of infected on a given day does not simply equal to the daily reported cases. While it may be more convenient to simply run the SIR model using daily case data, a more accurate approach involves estimating the number of infected individuals at any given time. Using our γ estimation –a 7.5-day average treatment window– we aggregate daily cases data to give us an estimate of the number of active infections on each given day.

Fitting SIR model

Fitting a compartment model such as SIR, is a numerical challenge. The curve-fitting is usually achieved by solving a set of differential equations using the Runge-Kutta algorithm [29,30]. In our study, we are interested in how the effective contact rate of the infection, β, is changing according to mobility. By fixing $\gamma=1/7.5$, we set out to determine β that minimizes SSE.

Our mobility data starts on 2/28/2020 and ends on 4/17/2020, covering a total of 7 weeks. For each country, using consecutive starting and ending weeks, we estimated corresponding βs of the SIR model (182 β values).

When estimating the β values, we used "Multi-Level Single-Linkage"[31], Subplex (Nelder Mead algorithm on the sequence of subspaces)[32], and BFGS quasi-Newton method [33] algorithms to check for consistency of the error minimizing β parameter and reported the best in terms of MSE error. With no exception, all methods yielded identical β values, indicating the numerical stability of the fitted curve.

Machine learning setup

As the last step of the ETL process, we merged mobility data with SIR model fits (β values) by adding a one-week delay period to measure the effects of mobility on the overall fit of the model. Larger β values indicate a larger, faster spread ($R_0 \propto \frac{\beta}{\gamma}$). A graphical summary of data merging and the study methodology is provided in the supplemental materials.

We investigated the relationship between β and mobility factors by looking into the predictive power of mobility with respect to β. Since the mobility factors were highly correlated, instead of training OLS regression models, which may raise multicollinearity concerns, we used the data to train a Gradient Boosted Trees (GBT) model for regression.

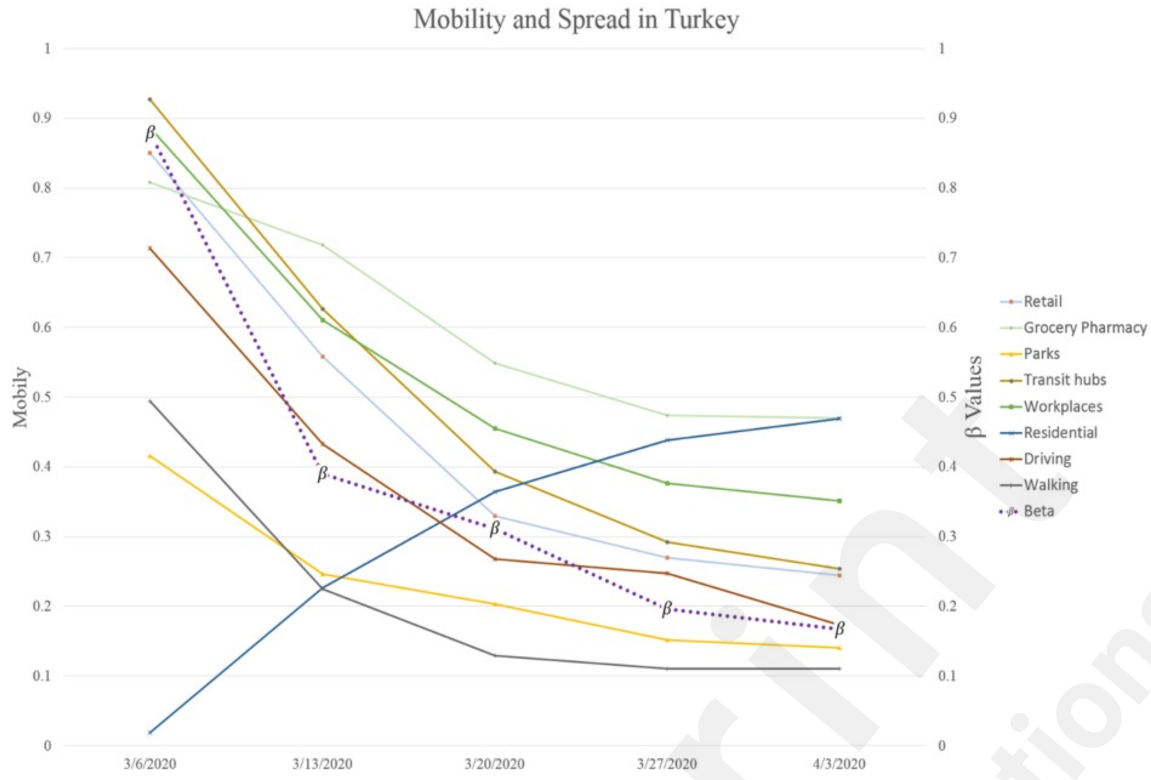
GBT is a boosting ensemble machine learning approach that sequentially constructs a large number of decision trees; in each sequence, the algorithm reweights the training data based on the model performance in the previous sequence (giving a higher weight to instances with a more substantial error term). According to Hastie et al. [34], GBT, due to its stepwise greedy strategy for selecting features in growing trees, automatically disregards redundant features at any step, hence is robust to multicollinearity.

Due to our limited sample size (n=130; 26 countries, five weeks per each), we employed a leave-one-out strategy for validating the GBT models. Each time we had the algorithm to sequentially grow 2,000 trees with a learning rate of 0.01 using 129 data points and tested the model on the other one.

Moreover, in order to assess the importance of each single mobility variable in determining changes in β, we then looked into the feature importance report provided by the GBT algorithm. For each predictor variable, the report provides a score indicating how valuable that variable was in the construction of the decision trees within the model. The more a feature is used in splitting the tree nodes, the higher its relative importance. A detailed discussion on how each score is calculated is provided in [34]. The results are described next.

Results

While the mobility trends indicate lower mobilities, limiting mobilities results in increased residential mobilities across almost all countries. Figure 1 shows a graphical depiction of our expected results. It can be visually observed that β values mimic the mobilities of the earlier week. In the UK, for instance, while reduced mobility in earlier weeks resulted in a slower spread, a slight increase in mobility resulted in the growth of spread speed (larger β).



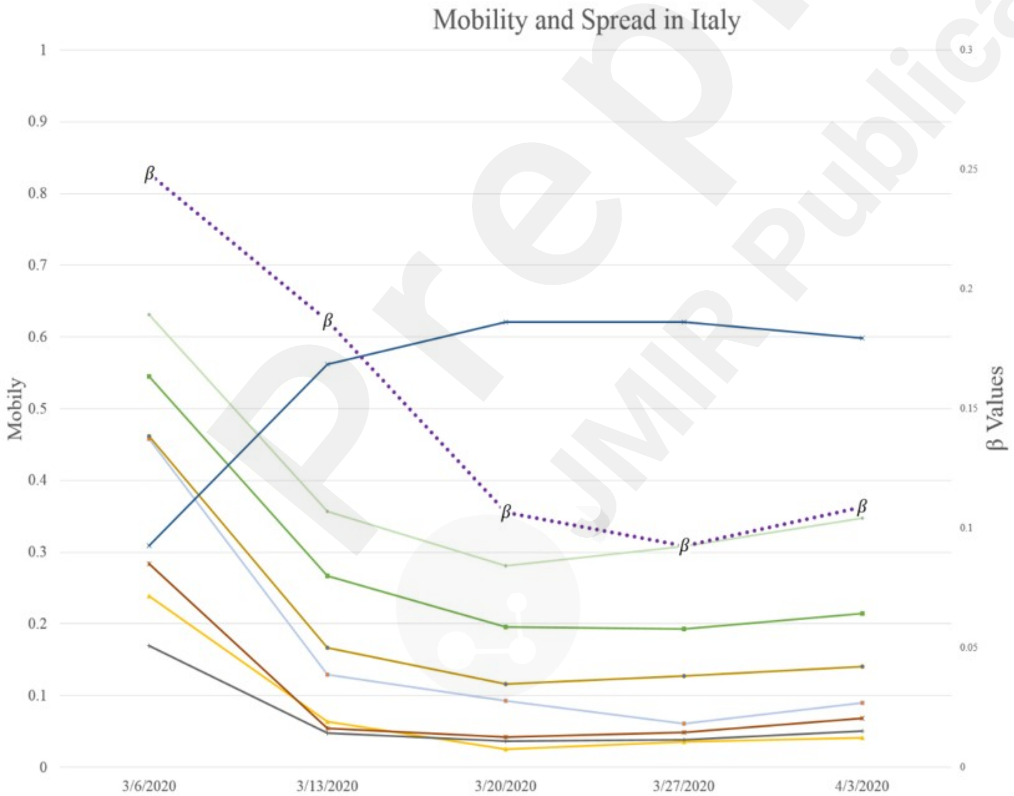


Figure 1- Mobility and spreads after lag are taken into account (β values correspond to the week after the indicated date on the x-axis).

The GBT regression analysis results suggest that the mobility factors were able to explain around 47% of variation in COVID-19's transmission rate (β) changes. Mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) of β predictions were 0.06, 0.005, and

0.072, respectively.

Figure 2 indicates the relative importance score of each mobility feature obtained from the GBT algorithm.

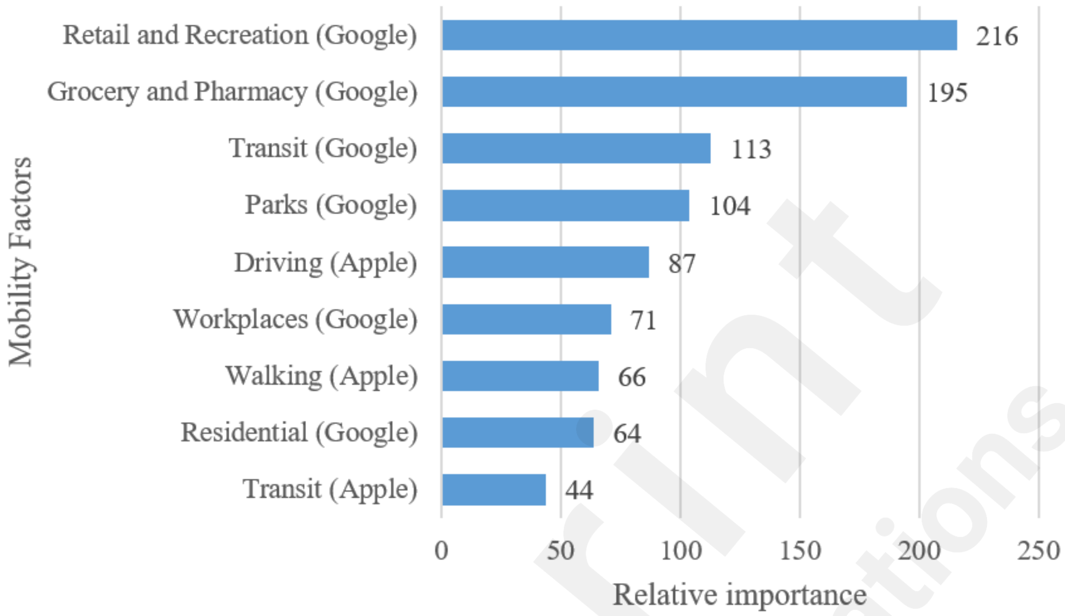


Figure 2- Relative importance of mobility factors in determining the COVID-19 transmission rate.

Discussion

The present study seeks to provide a more realistic and generalizable assessment of the effectiveness of social distancing interventions (reflected in mobility pattern changes) in controlling the spread of disease at the time of pandemics. Our results show that around 47% of the variation in the disease transmission rate is explainable by changes in mobility patterns resulted from enforcing social distancing policies in the studied countries.

Also, as shown in Figure 2, changes of mobility in public places such as retail and recreation centers (e.g., restaurants, cafes, theaters, etc.), grocery stores and pharmacies, transit hubs (e.g., airports, bus stations, subways, etc.), and parks are the most important determinants of β, the disease transition rate. Also, interestingly mobility in residential areas (the least public area) turned out to be the second least relevant factor in predicting β. It should be noted that the “Transit” mobility variable from the Apple Inc. data contained only zero values for 8 out of the 26 countries. Since they were not marked as missing in the original data set, we used them as is. However, it is highly likely that they were supposed to be missing values, in which case most probably the Residential mobility variable could have been the least important predictor of β. Overall, this justifies the governments’ policy to force restrictions on travel, restaurants, and public events with the aim of controlling the spread of the disease.

Social distancing is an umbrella term that involves several different types of interventions, including case isolation, school closure, quarantine, distance working, and contact reduction in public places. Changes in mobility patterns, whose effect was investigated in this research, can be considered as a surrogate measure of multiple social distancing interventions at the same time. Since the focus of other similar studies (mostly simulation-based) is on different combinations of these interventions, also different criteria used to report the effect in those studies, comparing our results to theirs seems challenging. For instance, Koo et al. [14] have used different combinations of reproduction numbers and interventions and reported the mitigating effect in terms of *reduction in the number of infections* (between 78% to 99%); or Milne and Xie[15] have looked into several interventions, one at a time, and reported the mitigation role in terms of *reduction in the proportion of population infected* (from 66% down to 24%); whereas this study uses the disease's *transmission rate* β as the criteria to report the efficacy of social distancing.

From a theoretical viewpoint, this study contributes to the literature by proposing an approach for utilizing real data, as opposed to simulated numbers, to study the effect of various interventions at the time of epidemics. We acknowledge that our results are highly affected by the lack of sufficient data (primarily due to the recency of the COVID-19 pandemic and enforcement of social distancing policies); however, it still provides solid evidence on the effectiveness of social distancing. We argue that our results involve a considerably lower degree of uncertainty due to its reliance on real transactional data, which has already captured the complex dynamics of the epidemic. Also, since our data is not limited to a specific geographical area, our results should be more generalizable than similar studies, mostly limited to a certain area.

While different countries, due to differences in their public health policies and/or health care infrastructures, might be inconsistent in terms of the number of tests they perform and consequently to report the number of infections, we argue that since our approach only considers within-country changes for estimating the transmission rates, it is fairly robust to such inconsistencies. Also, obtaining the exact same β estimates from three different optimization algorithms shows that our estimates are robust with regard to the estimation methods as well.

Due to relying on real transactional data, we argue that this study provides a less noisy assessment of the efficacy of social distancing interventions than similar simulation-based studies. This is especially due to the complex nature of epidemics that makes researchers who take a simulation approach to estimate several dependent parameters (e.g., estimating mortality rate depends on the number of infections, which itself depends on the transmission rate and the susceptible population), each based on a set of assumptions which might be too simplistic in some cases; whereas each of those estimations might involve a reasonable error, their dependency leads to the introduction of a relatively high accumulated error in the whole study. Due to this complexity, most simulation-based studies are only focused on the efficacy of a single social distancing policy (e.g., Earn et al. [7] only look into school closure). Using real data, on the other hand, eliminates some sources of error by reducing the need for multiple estimations.

Also, due to the cross-national nature of the data, our results are more generalizable than similar studies mostly conducted in a certain geographical area. Whereas countries may prefer to study the effect of their policies in their own situations, we argue that by fitting a single model to a multi-country data set we mitigate the country-level idiosyncrasies in data, thereby let the policy makers a clearer picture as to how mobility is linked to the speed of the disease spread.

From an empirical standpoint, in addition to providing supporting evidence for the effectiveness of social distancing policies, our study provides specific insights for the policy-makers as to which category of locations and activities to be considered as top priorities for enforcing social distancing measures. Notably, our investigation revealed that mobility changes in highly public places such as restaurants, cafes, grocery stores, transit stations, and parks play a more important role in decreasing the disease spread compared with workplaces or residential areas.

Additionally, our results suggest that reductions in "driving" mobility are relatively more important than changes in "walking" patterns in determining (decreasing) the disease spread. This also makes sense since the geographical span of driving mobility is normally far wider than walks, therefore makes a susceptible person subject to a relatively higher risk of infection (due to potentially higher infected population resided in a wider area). This suggests that governments' restrictions on driving (especially long-distance) may effectively reduce the number of new infections.

In addition to the relatively small sample size, another limitation of the present study is its reliance on highly aggregated data at the country level. Whereas this was mainly because of unavailability of granular mobility and/or COVID-19 data at the present time, we believe that replicating the proposed approach using a more granular mobility data set (in terms of the type of activity and/or categories of places) could possibly reveal more interesting facts with regard to the effectiveness of specific social distancing policies. So we encourage future researchers to extend the present study upon the availability of such data.

In the end, we believe that this study sheds light on the high potential of technology innovations in studying pandemics. Whereas we only took a retrospective approach by using historical geolocation data, a proactive approach that uses tracking technologies to identify people and/or locations at high risk could help governments and public health policy-makers to be well prepared for similar pandemics in the future. As a very recent effort, Google and Apple have announced a collaboration for implementing a contact tracing system to send automatic mobile phone alerts to people who have recently been in close contact with those who tested positive for COVID-19 [35].

Conclusion

Our analyses of real mobility and COVID-19 data provide substantial evidence on the significant mitigating role of social distancing interventions on the disease transmission rate. Particularly it is shown that controlling people's attendance and mobility in highly public places as well as enforcing driving restrictions are effective public health policies to help flatten the curve.

Conflicts of Interest

None declared.

Abbreviations

COVID-19: Corona Virus Disease of 2019
SIR: Susceptible- Infected- Recovered
ECDC: European Centre for Disease Prevention and Control

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Supplementary Files

Figures

Multimedia Appendixes