Transport mobility restrictions as a pandemic response: a case study Germany

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Abstract

The COVID19 pandemic has caused a large number of infections and fatalities, causing administrations at various levels to limit public mobility. This paper analyzes the complex association between the stringency of restrictions, public mobility, and reproduction rate (R-value) on a national level for Germany. The goals were to analyze; a) the correlation between government restrictions and public mobility and b) the association between public mobilities and virus reproduction. In addition to correlations, a Gaussian Process Regression Technique is used to fit the interaction between mobility and R-value. The main findings are that: (i) Government restrictions has a high association with reduced public mobilities, especially for non-food stores and public transport, (ii) Out of six measured public mobilities, retail, recreation, and transit station activities have the most significant impact on COVID19 reproduction rates. (iii) A mobility reduction of 30% is required to have a critical negative impact on case number dynamics, preventing further spread.

Introduction

The COVID-19 virus first appeared in China in December 2019 and spread rapidly around the world. The World Health Organization (WHO) declared it a Public Health Emergency of International Concern in January 2020 and as a pandemic on March 11 [1]. As of the end of May 2021, it had cost 3.5 million lives worldwide [2-3].

The airborne nature of the virus meant that it was imperative to ensure that infected persons spread it to as few others as possible. The pivotal average number of other individuals that each carrier of the virus infects at a given point in time is defined as the reproduction value (R-value) [4-5]. The goal of lowering the R-value made it essential to reduce close contact between individuals , and most policy responses targeted social distancing and public mobility reduction. This was pursued through various means by national governments. Various countries or specific regions around the world have placed a wide variety of mobility restrictions to protect their populations from being infected. An international review of government interventions found that a combination of measures implemented at the right points in time was essential for curbing reproduction numbers [6].

General compliance with these policies could be estimated by observing the amount of traffic at public spaces of various kinds. For example, the current mobility could be measured through automated data collection implemented on a variety of platforms [7]. This allows for an estimate of the number of people passing at certain locations and is usually presented as daily aggregates.

Due to the variety in responses and reporting, the present study concentrates on the effects of policy implementation in a single country and use Germany as a case study for the dependencies between public policy, aggregate mobility, and virus contamination. According to the WHO, there were 19.9 million cases and 128,000 deaths in Germany through March 26, 2022. There were several national "lockdown"

periods in Germany with a combination of measures from the list enforced by work-at-home orders, mandatory closures of public and private establishments, and travel restrictions [8].

This study focuses on the associations between restrictions, public mobility and viral reproduction. The government response is related to loss of mobility and the spread of infections through a combination of correlation analyses and a machine learning technique (Gaussian Process Regression). The inferential measures are complemented by an estimation of threshold level of mobility required for keeping the R value below 1, i.e. containing further viral dissemination.

Background

Through prohibitions, public closures, and recommendations, citizens were forced or encouraged to spend less time near others and more time in a private sphere, while keeping the maximum size of private gatherings at minimum levels. The efficiency of restrictton measures can be quantified as to their isolated effect on reducing the R-value, and the most successful stringency measures appear to have been based on the premise of reducing human to human contact. For example, it has been identified that reductions in air, car, public and pedestrian travel had a strong association with falling R numbers [9], and that especially transport and workplace activity reductions was paramount for the reduction of community infection [10–11]. The predictive power of mobility alone as a determinant of Sars-COV2 transmission has been found to range between 30 and 80%, depending on the level of other applied restrictions [12].

The nonlinear nature and influence of external factors in the relationship between mobility and virus transmission make modeling of their interaction a complex task. While several conventional statistical approaches have been attempted [13–15], previous research shows indications that Gaussian Process Regression (GPR) models form a solid basis for models of virus spread [16–17]. In direct comparisons between the methods on COVID-19 data, GPR has been able to fit the data better than other machine learning methods like Support Vector Machines (SVM) or Decision Trees (DT) [18]. Due to its capacity to capture spatio-temporal variations combined with external factors, it can be considered the state of the art for modeling the geographical spread of diseases. This has been found also for other diseases such as malaria [19]. GPR seems to work well with small to moderate-sized datasets as in the COVID-19 pandemic (daily observations over slightly more than a year).

In this context, the contributions of the present study can be summarized as follows. First, the connection between stringency and mobility is quantified, identifying what sectors of public life are affected most by public restrictions. Second, the association between various mobilities and spread of the virus is established through correlation analyses, determining what mobilities has the most influence on the reproduction number. Finally, machine-learning analysis of mobility, vaccinations and temperature as predictors of virus spread determines a threshold to contain further spread of pandemic infections.

Method

Data Sources

Google Mobility utilisesdata from the Google Maps system and other platforms, it measures the amount of mobility in the categories in six categories presented in Table 1. The numbers are reported as the percentage change from a baseline level.

Table 1. Public mobility data categories.

Category	Inclusion
Retail and Recreation	restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters
Grocery and Pharmacy	grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies
Transit stations	subway, bus, and train stations
Parks	local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens
Workplaces	places of work
Residential	homes

The government-level of restrictions is quantified in a project known as the Oxford COVID-19 Government Response operated by the Blavatnik School of Government at the University of Oxford. It incorporates a wide variety of different restrictions related to social distancing in the wake of the pandemic and serves as a benchmark on how much each administration enforced lockdown. The Stringency Index is a weighted average of several categories [20], including school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls.

Temperature data were collected from the German Weather Service (DWD). The daily average at the Berlin-Tegel station was used as an aggregate for each day in the studied period.

R-values were obtained from the Robert Koch Institute derived from a now-casting model which has been used to forecast virus propagation on national and local levels [21]. Through time series analysis of the number of new cases per day, an instantaneous reproduction number can be derived retrospectively for each day [22].

The period of March 9, 2020 through June 22, 2021 was studied.

Mobility Correlations

Spearman correlations were used to identify associations between:

a) Oxford Stringency Index and the various mobilities

b) Mobilities and reproduction values

Gaussian Process Regression

An exponential–logarithmic model has been identified as an adequate fit for the association between community mobilities and reproduction rates [23-24], i.e. the logarithm of the R-value is dependent on aggregate mobility. It has also been identified that both temperature and level of vaccinations have an impact on reproduction [25-26].

Gaussian Process Regression (GPR) is a nonparametric supervised machine learning method usually applied to multivariate classification and regression problems [27]. GPR is used for describing the original distribution for flexible classification and regression models, where regression or class probability functions are not only simple parametric forms. One of the main advantages of the Gaussian process is the diversity of covariance functions that leads to the formation of functions with distinct types or degrees of continuous structures and enables choosing the proper selection.

Based on these previous findings it was possible to fit a GPR model for the relationship between mobility, temperature, and vaccinations with the following setup:

Kernel function: Exponential , Kernel scale: 14.396 , Signal standard deviation: 0.230 ,

Training data: 80 % of observations, randomly chosen, Test data: Remaining 20 %

Results

4.1. Government stringency

The Oxford Stringency Index calculates stringency as a weighted index of government response related to nine factors: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls.in four dimensions. Estimated levels of stringency of German policy are on display in Fig. 1, on a scale from 0 (no restrictions) to 100% (maximum lockdown).

Restrictions were ramped up quite rapidly to a high level during the first lockdown and then relaxed over the Summer months, only to be reintroduced at an even higher level during the winter of 2020/2021 in the

“second wave”. The stringency then remained quite intrusive through the Summer of 2021. Some descriptives of the studied period can be found in Table 1.

Table 1
Stringency characteristics.

	Mean	Standard deviation	IQR
Government Response	60.9	7.6	56.5–66.8
Containment	63.7	8.2	58.0–70.8
Economic Support	41.3	12.2	37.5–37.5
Overall	67.2	12.0	59.7–76.8

4.2. Public mobilities

Public mobilities measured in percentage change from the baseline in the six categories (Table 1) are in Fig. 2.

Activity at workplaces, retail and recreation, and public transit stations was well below ordinary levels through the period, while parks rose during the Summer and residential mobilities was constantly higher due to more work from home arrangements. Some overall characteristics of each type of mobility in the studied period can be found in Table 2.

Table 2
Aggregated changes in public mobilities.

	Mean / % change	Standard Deviation / %	IQR / %
Retail and Recreation	-30.8	22.2	-49 - -10
Groceries Pharmacies	-3.1	20.1	-6–3
Parks	49.4	51.6	4.5–81.5
Transit Stations	-31.4	14.4	-42 - -21
Workplace	-23.3	16.3	-31 - -16
Residence	8.3	5.4	5–11
The biggest shift came away from workplaces, public transport and non-essential shopping, as the imposed lockdown measures targeted.			

4.3. Correlations Analysis

To compare the efficiency of the implemented policy measures and evaluate what sectors had the most impact on virus propagation, an attempt to quantify the association between government stringency, R-

value, and each of the six mobilities. Spearman correlations between daily values of overall stringency and public mobilities were calculated, and presented in Table 3.

Table 3
Correlations Stringency and mobilities.

Mobility type	Correlation with Stringency
Retail and Recreation	-0.85
Groceries Pharmacies	-0.31
Parks	-0.59
Transit Stations	-0.83
Workplace	-0.39
Residence	0.75

It was found that a higher amount of stringency had the strongest negative impact primarily retail (-0.85) and transit (-0.83) sectors, while more restrictions also were associated with more time spent at home (0.75).

For the link between mobility and viral spread, Spearman values can be found in Table 4.

Table 4
Correlations Stringency and mobilities.

Mobility type	Correlation with reproduction
Retail and Recreation	0.45
Groceries Pharmacies	0.20
Parks	0.11
Transit Stations	0.42
Workplace	0.15
Residence	-0.27

The clearest associations were again between mobilities in the retail (0.45) and transit (0.42) sectors, respectively, where increased levels of mobility led to higher R-values. More time spent in the residence slowed virus reproduction (-0.27), while especially parks and workplaces had a rather small impact.

3.5. GPR Model Fit

An evaluation of the model fit of GPR on the test set is presented in Table 5.

Table 5
GPR Model Fit Results.

RMSE	MAE	MSE	R2
0.14	0.093	0.018	0.83

RMSE = Root Mean Squre Error; MAE = Mean Absolute Error; MSE = Mean Square Error; R2 = Coefficient of Determination

The GPR with an exponential kernel captures the modeled relationship more accurately than the conventional method as it leads to a closer fit and lower prediction errors, along with a coefficient of determination above 80%.

3.4 Mobility Thresholds

The reproduction rate was associated primarily with variations in mobilities for (i) retail and recreation (ii) transit stations. Based on this, it was possible to estimate the probability for an R-value under one based on retail mobility, in Fig. 3.

The graph indicates a 30% reduction of mobility as necessary for a higher than 50% probability of R being below 1.

Discussion

The highest correlation between mobility and reproduction was identified for retail and transport, as these sectors seem to be the most pivotal for containing the virus. These would be perceived as non-essential and tend to gather considerable amounts of human beings in small inside spaces, especially during peak hours. These results still need to be confirmed beyond the German example, where other behavioral patterns might be more prevalent. The goal of restricting community spread by containing R-values below one with at least 50% chance required a reduction of 30% in retail or transit mobilities, similar to previous results .

It was expected that higher mobilities would lead to more reproduction and that vaccination would drive the number in the opposite direction, matching common theories on virus propagation. The negative association with temperature was also in line with anticipations, as the virus is known to spread at higher rates in lower temperatures. As indicated by the high rise in parks mobility in the Summer months, people are also spending a higher share of their time outdoors during warmer periods, making them less prone to infect others.

Conclusions

Understanding the relationship between stringency, mobility, and infection rates have been crucial for coping with the worldwide outbreak of COVID-19, and German data for the period from March 2020 to

June 2021 served as an example. Higher correlation between activity at retail/recreation and transit locations and virus propagation points to public transport, workplaces and cultural meeting points as areas of high importance for mitigating the pandemic. It appears that the German official strategy to contain these by closing a large number of cultural and recreational establishments and reducing utilization of public transport through stay-at-home orders was well-founded, while activities at workplaces, parks, and grocery stores had less impact.The targeted level of 30% should serve as a benchmark threshold for necessary mobility reductions in future similar outbreaks.

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Ethics Approval: All data was based on human surveying and downloaded from publicly available data sources, where ethics permission had been obtained.

Consent to participate: No human subjects are involved, as the manuscript is relying solely on public data for stringency, reproduction number and mobility.

Consent to publish: See above

Figures

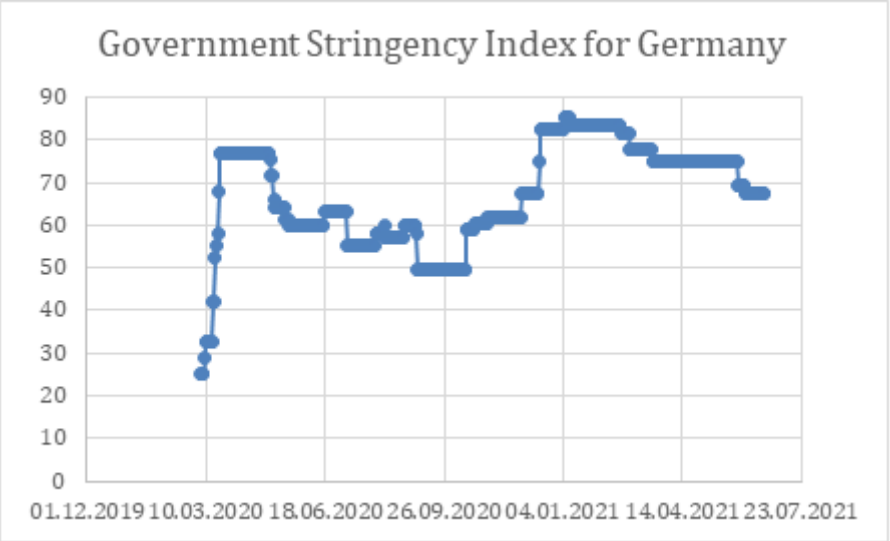

Figure 1

Government Stringency.

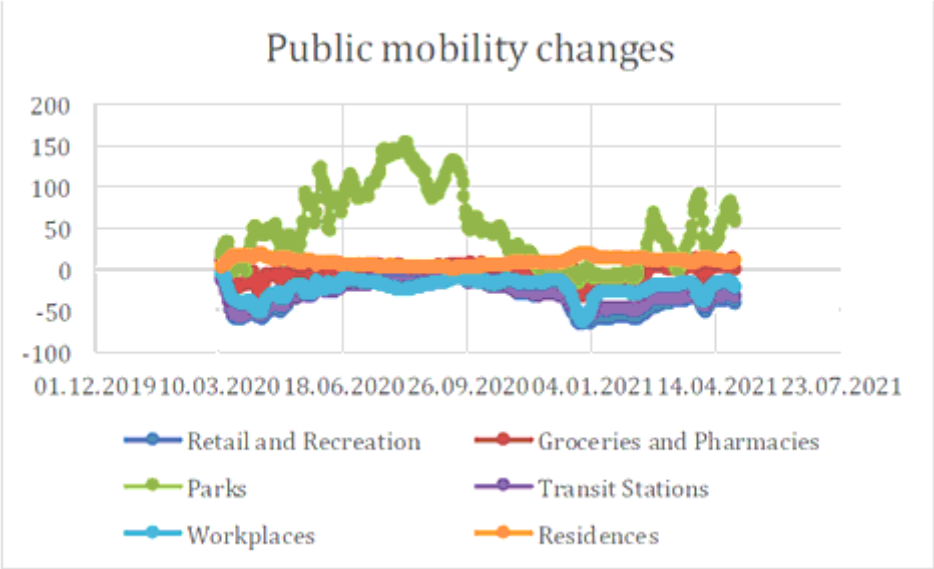

Figure 2

Public mobilities.

Figure 3

Estimated probability of R below spread levels based on retail mobility.