Lockdowns may lose up to half of their impact on mobility after a month

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Abstract

As the novel coronavirus (COVID-19) pandemic spread across the world over the past year, to mitigate its spread many countries imposed lockdowns in the form of stay at home requirements on their citizens. Here we analyze data from 113 countries to investigate the effectiveness of such lockdowns in terms of the immediate reduction in mobility achieved upon implementation, as well as the evolution of mobility levels throughout the duration of lockdowns. First, we observe that while imposing a lockdown has a significant initial effect of reducing mobility, this effect wears out over time, suggesting a fatigue effect. On average, we find that up to half of the mobility reduction achieved after a lockdown may be lost after one month. Second, we show that countries which achieved a higher reduction in mobility when lockdowns went into effect were also the ones where fatigue was stronger. Third, we report that countries with higher life expectancy not only had a higher reduction in mobility when lockdowns went into effect but also had a lower fatigue. Fourth, we note that higher income inequality was associated with higher reduction in mobility at the start of the lockdown. Our findings can inform policy makers in anticipating the likely longevity of their stringent lockdown policies and help them be more effective in planning by accounting for lockdown fatigue.

The United States recorded its first confirmed case of the novel coronavirus disease (COVID-19) in late January, 2020 in the state of Washington.[1] By the end of January, thousands of cases were observed in China and cases appeared to be spreading globally, leading the World Health Organization (WHO) to declare COVID-19 to be a Public Health Emergency of International Concern.[2] By March, COVID-19 had spread to over a hundred countries with over a hundred thousand cases and more than four thousand dead, further leading the WHO to declare it a global "pandemic". [3]

As COVID-19 spread globally, governments in many countries started instituting formal policies with the aim of mitigating the potential outbreak and loss of life within their individual jurisdictions. Starting with travel advisories and travel restrictions, the policies quickly escalated to more severe actions such as stay at home requirements (SHR) which we refer to as lockdowns. The intent of imposing lockdowns was to restrict and reduce the movement of citizens, which in turn would lead to lower contact among people, and hence to lower cases and lesser loss of life. [18,19] Indeed, scholars have analyzed the impact of mobility on the spread of the disease and shown that a reduction in mobility can slow the spread. [4,5,6,10]

At the same time, many have questioned the appropriateness of governments imposing lockdowns and the general efficacy of lockdowns and quarantines. [21] The editorial board of the Wall Street Journal publicly opined "*These shutdowns are extraordinary and have costs, not least the harm to small business owners. Americans may simply decide to ignore the orders after a time. Absent a more thorough explanation of costs and benefits, we doubt these extreme measures will be sustainable for long as the public begins to chafe at the limits and sees the economic consequences*". [7] More generally, research shows that government policy, the alignment of public interests, and compliance interact closely. [17,20] In this research, we specifically focus our attention on the broader issue of whether and to what extent have lockdowns been effective in terms of achieving their objectives of reducing mobility.

A casual observation of the policies adopted by governments around the world suggests that the severity of the rules as well as the extent of their enforcement has varied significantly across countries. At the same time, the effects that these lockdown policies had on subsequent mobility has also been varied. Motivated by these observations, in this work we investigate the following research questions: [i] How effective are lockdowns in reducing mobility? [ii] Is their effectiveness long-lasting, at least during the time when they are in effect? [iii] If there is variation in their long-term effectiveness across countries, what mobility patterns and country characteristics explain these differences?

Our work contributes to a growing body of research analyzing the impact of government policies on factors such as mobility. [12,13] Prior research has found that government policies as well as pandemic severity impacts social distancing that is practiced within communities, and that less social distancing is practiced after observing local mitigation. [8] Researchers have also shown that social distancing and lower population density may be associated with decreased spread of the coronavirus. [14] Other work has shown that risk attitudes can be a critical factor in predicting mobility reduction, and that regions with more risk averse attitudes may be more likely to change behavior in a pandemic. [9] Compliance with mobility restrictions have also been shown to be associated with social connections and partisan beliefs. [15,16] We focus on the impact of lockdowns on mobility and characterize the extent and dynamics of the reduction in mobility achieved by imposing lockdowns in countries across the world.

Empirical Approach

To study the impact of lockdowns on mobility we analyze policy and mobility data for 113 countries. For each country, we identify the first time that a general requirement to stay at home (i.e., a lockdown) is imposed on its citizens and its duration. Using the metric of mobility at workplaces, we compute a baseline level of mobility prior to the start of the lockdown for that country to understand mobility levels before restrictions went into effect. Via a linear regression model that controls for day-of-the-week effects we characterize the initial reduction of mobility right after the implementation of a lockdown and its evolution throughout the duration of this requirement. The latter measures the change in the mobility metric for every additional day that the requirement remains in place. As shown in the results section, for most countries this mobility change is found to be positive, implying a wear out effect of the lockdown, which we refer to as lockdown fatigue. Via further regression analyses, we assess whether differences across countries in mobility responses to lockdowns in terms of initial mobility reduction and fatigue can be explained by country characteristics such as demographics and socioeconomic indicators.

Mobility levels are lower during lockdowns

To understand mobility patterns over the past year, regardless of policy or other interventions, we first compute the average mobility by month in each country for all 113 countries under study and generate a boxplot of these averages by month (Figure 1). During the initial phase, we observe a global median decline in mobility of 17.4 and 45.7 percentage points in March and April 2020 respectively, compared to the baseline reference levels of January-February 2020. This is followed by a pattern of gradual and partial recovery that extends through June 2020, with mobility levels remaining relatively stable thereafter.

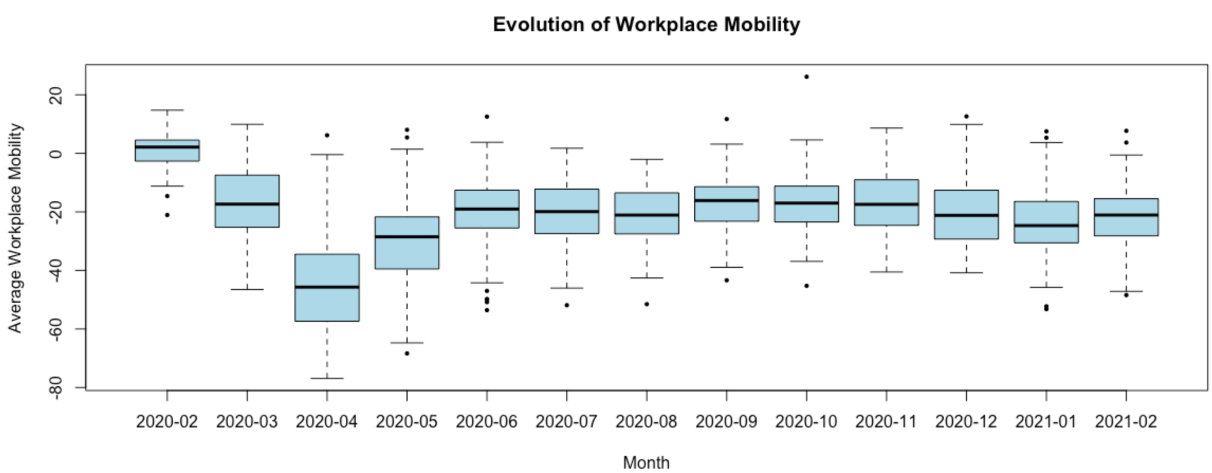

Figure 1: Evolution of workplace mobility. Boxplot of the average workplace mobility observed for each country in that month (n=113 countries). The solid line in the box indicates the median, with boxes at the interquartile range. Whiskers are either at 1.5*(interquartile range) outside the box, or at the extreme value.

Next, we visualize the implementation of lockdown policies across the world as measured by the proportion of countries in our sample that are under lockdown on any given day (Figure 2). Interestingly, the mobility decline and recovery observed in Figure 1 coincides with the implementation and subsequent relaxation of lockdowns observed in Figure 2. The highest proportion of countries requiring their citizens to stay at home is observed during April 2020 (69.9%). This proportion stayed at high levels during March to May 2020, and then decreased to lower levels in June 2020, and stayed low for a long time thereafter.

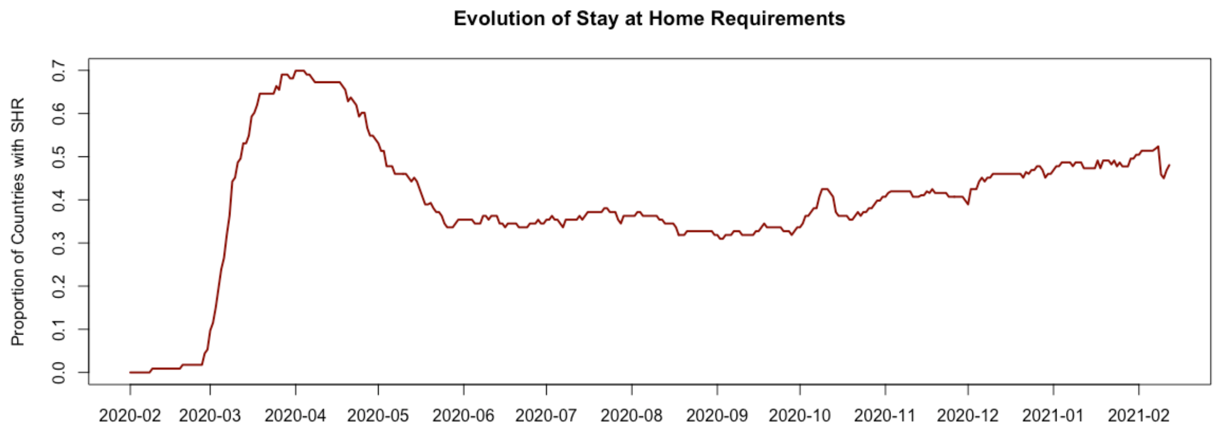

Figure 2: The proportion of countries with a lockdown. The daily fraction of countries that have an active stay-at-home order for its general population (n=113 countries).

Lockdowns have a strong initial impact and then fatigue sets in

While at a macro level the prior two figures may suggest that lockdowns are effective, a closer look at the evolution of mobility levels during lockdown periods for each country reveals a more nuanced story. Figure 3 shows that on average, lockdowns achieve a strong initial reduction in mobility but then are followed by a wear out period suggesting that lockdown fatigue is setting in. Mobility is reduced on average to 39.4% below the baseline at the start of a lockdown, and then to 53.5% two weeks later. Nevertheless, this initial impact exhibits a wear out effect, as mobility gradually rises on average 3 percentage points with each additional week that the lockdown stays in effect. After 60 days of lockdown, the average mobility levels rise to 37.3% below the baseline, effectively erasing all impact of the lockdown, even though the lockdown continues to stay in effect.

As one may expect, the duration for which lockdowns are imposed varies across countries. Hence, it could be hypothesized that the fatigue observed in Figure 3 (black dots) might arise due to a selection effect if countries for which a lockdown is less effective at reducing mobility lift the lockdown earlier. However, an analysis focusing only on those 37 countries where the lockdown was in place for at least 60 days (red triangles in Figure 3) reveals that the wear out pattern still continues to be present.

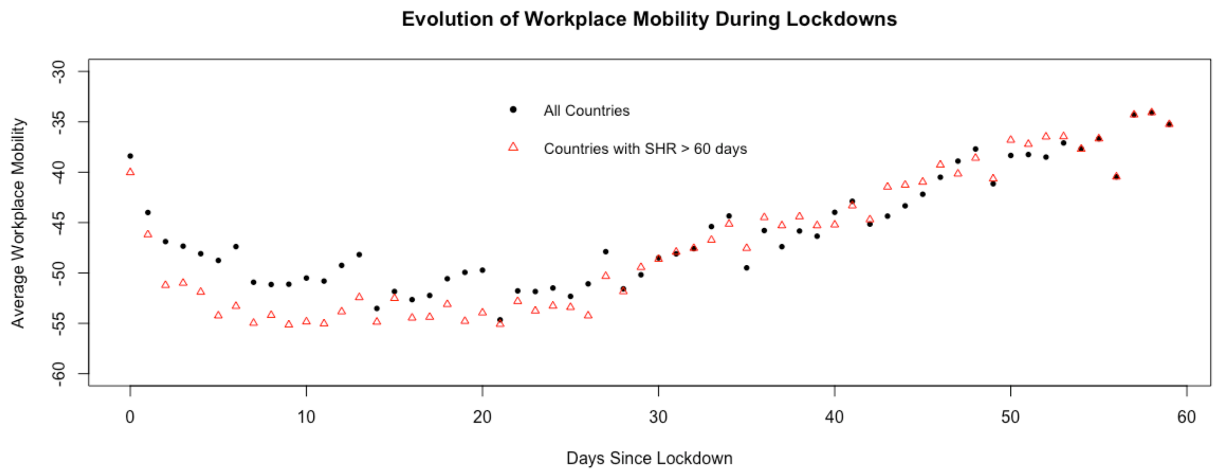

Figure 3: Evolution of workplace mobility during lockdowns. For each country, we identify the date when the first lockdown requirement was imposed over its general population. During the time when the lockdown was in effect, workplace mobility for each day since the beginning of the lockdown is averaged across all n=81 countries for which a lockdown was observed. These results are shown in the "All Countries" time series with solid dots. As a robustness test, we repeat this analysis for a subsample of n=37 countries where the first lockdowns lasted for more than 60 days. These results are shown in the time series with hollow triangles.

To better understand the country level dynamic effects of imposing a lockdown on mobility, we specify a regression model that explains the observed daily mobility level within a country as a function of the days since the lockdown was imposed, after controlling for day of the week effects (additional details provided under Materials and Methods). This provides us with a country level estimate for the initial reduction in mobility level at the start of the lockdown, as well as a fatigue metric which indicates the daily wear out rate at which mobility increases while the lockdown is in place (Figure 4). We observe that for all but 5 countries the estimated wear out rate is positive; and for 42 out of these 60 countries it is significantly positive ($p<0.001$) implying lockdown fatigue. On average, lockdowns yield a reduction in mobility of 46.7% below mobility levels prior to the start of a lockdown. To quantify the effects of fatigue, we compute how much of this reduction in mobility is sustained over time. We find that up to half of this improvement may be lost in a month due to fatigue.

Higher initial mobility reduction is associated with higher fatigue

Figure 4 reveals a significantly negative correlation between the mobility levels at the beginning of the lockdown and subsequent fatigue (correlation -0.64, $p<0.001$). This suggests countries that begin their lockdown with a stronger initial reduction in mobility levels approach higher levels of mobility more rapidly as the lockdown continues to be in effect.

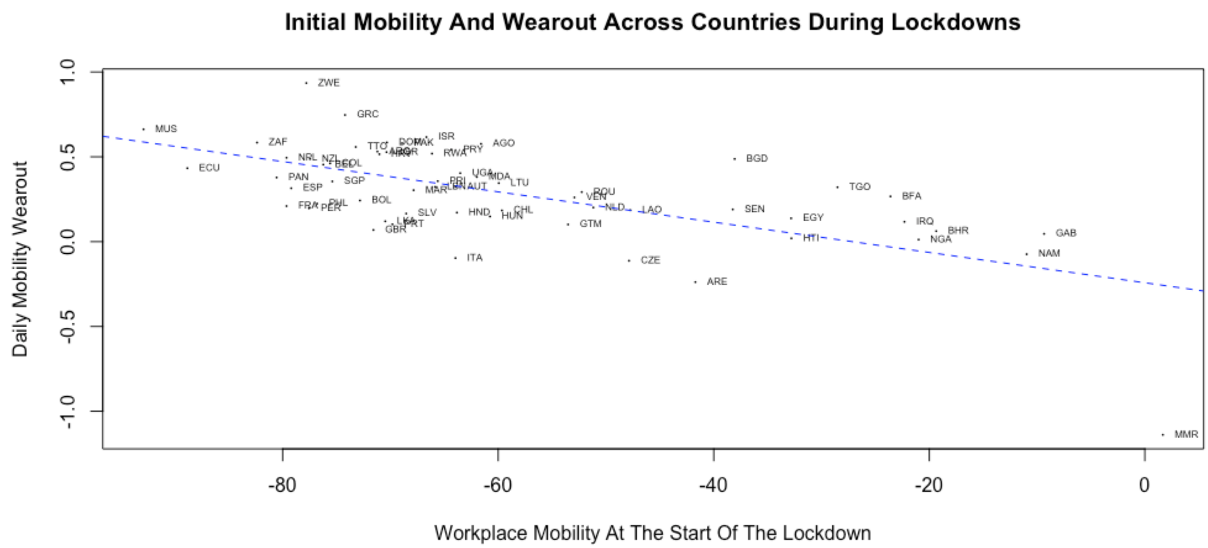

Figure 4: Mobility dynamics across n=60 countries in a lockdown. The horizontal axis represents the country level estimate for workplace mobility at the start of the lockdown. The vertical axis represents the country level estimate for fatigue, i.e., the daily change in workplace mobility during the lockdown.

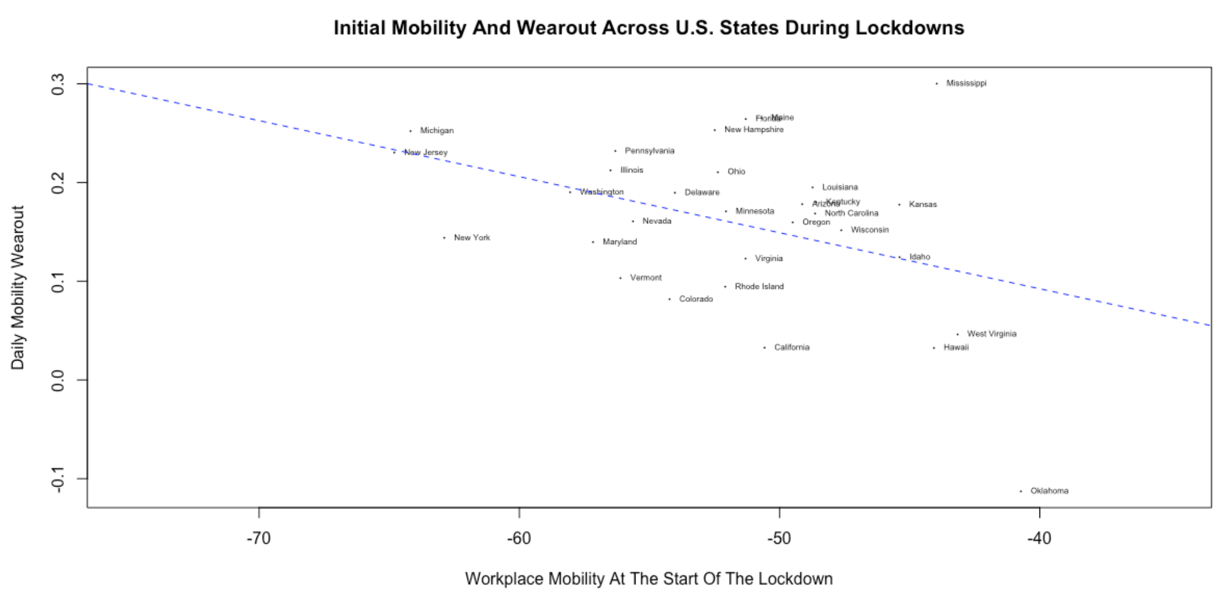

Figure 5: Mobility dynamics across n=31 US states in a lockdown. The horizontal axis represents the state level estimate for workplace mobility at the start of the lockdown. The vertical axis represents the state level estimate for fatigue, i.e., the daily change in workplace mobility during the lockdown.

This pattern of initial mobility reduction followed by the onset of fatigue that is observed across multiple countries is also replicated when looking at smaller geographical regions (Figure 5). Along similar lines as before, we study the evolution of mobility for 31 US states that implemented a general lockdown for at least one month. We verify that for 30 of these US states the wear out effect is positive, and significantly positive (p<0.001) for 24 states.

Our earlier analysis showed that across 60 countries there exists substantial variation in the reduction in mobility achieved at the start of the lockdown as well as in the fatigue or daily wear out observed during the lockdown. We next explore whether country characteristics help explain some of this variation.

Country characteristics and mobility dynamics

Regression analyses with initial mobility reduction and daily wear out rate as the dependent variables reveal interesting insights regarding the potential role of country characteristics in explaining mobility dynamics. While initial reduction in mobility at the start of the lockdown was a significant factor in explaining fatigue, so was mobility level before the lockdown and life expectancy (supplementary Table 2). Specifically, countries with higher life expectancy were associated with a significantly lower fatigue. Higher life expectancy was also significantly associated with lower levels of mobility at the start of the lockdown (supplementary Table 1). In addition, a higher Gini coefficient (i.e., more income inequality) was also significantly associated with lower levels of mobility at the start of the lockdown. Not surprisingly, the level of stringency before the lockdown went into effect also shows a significant relationship with the mobility reduction observed during lockdowns (supplementary Table 3a and 3b). Higher stringency index before the lockdown was associated with a weaker reduction in mobility. This is presumably because a higher stringency index before the lockdown is also associated with lower levels of mobility prior to the lockdown. Finally, a higher human development index was associated with lower levels of mobility prior to the lockdown (supplementary Table 4).

Discussion

Overall, our global analysis suggests that lockdowns work, in that imposing a lockdown is associated with a significant reduction in the observed levels of mobility. Interestingly though, mobility dynamics in response to a lockdown vary significantly across the world. We observe and quantify a global pattern of lockdown fatigue, as mobility levels slowly start rising the longer a lockdown stays in effect. Furthermore, in a relatively short of amount of time (e.g., one month), lockdown fatigue may eliminate up to half of the gains achieved in terms of reduced mobility. A direct implication of this result may be that lockdown compliance may need to be reinforced by governments when they remain in effect for longer periods of time.

In terms of the drivers of lockdown fatigue, the strongest explanation for the wear out effect appears to be the initial reduction in mobility achieved at the start of the lockdown: the lower this initial mobility, the higher the fatigue. In some sense, these two appear to be compensatory: if a high amount of mobility reduction was already achieved prior to or at the start of the lockdown, then fatigue was higher as well.

Compliance with lockdowns in terms of the extent of reduction as well as fatigue observed varied significantly across countries. Higher life expectancy, more income inequality, and a higher human development index were all associated with more compliance. Specifically, fatigue was lower where life expectancy was higher. Mobility levels at the start of lockdown were lower where life expectancy and income inequality were higher. Where mobility levels were already low before the lockdown, the drop in mobility levels due to the lockdown was not as much. And in terms of voluntary compliance prior to lockdowns, reduced mobility levels were observed in places where the stringency index and the human development index was higher.

Our analysis has several limitations. First, we do not intend to make any causal claims; our findings are based on summarizing and regressing available data across sources to study the interplay between government policy and mobility. Second, our inferences of mobility are based on workplace mobility data, and while other mobility types have a strong positive correlation with this metric, it may be beneficial to further investigate the impact of lockdowns on other types of mobility. Finally, in this research we do not incorporate the explicit impact of case data on mobility. It is likely that beyond policy, observing actual cases in their communities may have a further impact on people's decisions to move around. Nevertheless, we hope that our findings above help inform policy makers on the nature of response they may expect when implementing lockdowns and incorporate these observations for more effective planning purposes.

Online content

Methods, materials, details about source data, the regression analysis results, and additional supplementary information are provided online.

Data Availability

The data that support the findings of this study are publicly available online at:

- Google: https://github.com/GoogleCloudPlatform/covid-19-open-data
- Oxford: https://github.com/OxCGRT/covid-policy-tracker
- UNDP: http://hdr.undp.org/sites/default/files/2020_statistical_annex_all.xlsx

Code Availability

Software used includes R (version 4.0.3) and RStudio (version 1.4.1103) for data analysis and model estimation. The code will be available from the authors upon request after publication (and for review).

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Materials and Methods

Data: The data used in this research was compiled from three sources:

[1] Google COVID-19 Community Mobility Reports: This dataset was accessed on March 2nd 2021, and provides daily mobility data, relative to a baseline level of mobility as measured during a reference period of January 3 to February 6, 2020. Mobility measures were constructed by Google using mobile devices of users who have opted in to Location History for their Google accounts. There are six distinct mobility measures: workplace, retail & recreation, grocery & pharmacy, parks, transit stations and residential. The first five are highly and positively correlated with each other, while the sixth is negatively correlated with the first five measures. Of these measures, workplace mobility exhibits the fewest missing values, hence we use this measure as our metric for mobility. This metric was available starting February 15, 2020 through February 26, 2021.

We focus on data aggregated at the country level, giving us 246 distinct entities labeled as countries, although some of these are territories such as Puerto Rico. For ease of exposition, we refer to these 246 territories as countries. Of these 246, we exclude countries that have missing values for workplace mobility and those that have a small population (less than 1 million), leaving us with 113 countries.

For each country, the data also includes characteristics such as population and geographical area.

[2] Oxford COVID-19 Government Response Tracker:[11] This dataset was accessed on March 2nd 2021, and provided daily policy data on when each country (or state in the case of US) began requiring its citizens to stay at home. Government policy data regarding stay at home requirements (SHR) is provided on an ordinal scale, where 0 is *no measures* are in place, 1 is government *recommending* not leaving the

house, 2 is the government *requiring* not to leave the house with exceptions for daily exercise, grocery shopping, and 'essential' trips; and 3 is the government *requiring* not leaving house with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc). We classify SHR levels 2 and 3 as being under a lockdown, since both these levels *require* a citizen to stay at home. A second variable in this dataset indicates whether SHRs are targeted to specific geographic regions (e.g., certain counties or regions), as opposed to being applied to the general population across the country. The final variable of interest from this dataset is the Stringency Index, which provides a composite score in the range of 0-100 (higher being more stringent) based on nine distinct policies related to school and workplace closings, cancellation of public events and public transport, restrictions on gatherings and on internal movements, on international travel, and whether the government is running public information campaigns.

[3] The United Nations Development Project (UNDP) data: This dataset was accessed on March 9th, 2021, and contains country level data on each country's human development index, gross national income per capita, life expectancy at birth in years, expected years of schooling, mean years of schooling and the Gini coefficient for income inequality. The human development index is a composite summary index of gross national income per capita, life expectancy at birth, expected years of schooling and mean years of schooling. The Gini coefficient is a measure of income inequality on a range of 0-100, where 0 refers to absolute income equality and 100 refers to absolute income inequality. When merging this data set with the previous ones, we manually checked for matching country names where needed.

Methods

The analysis for each country begins by identifying the first date when a lockdown is applied to the general population. Hence, we find the earliest date for which the variable C6_Stay at home requirements is at a level of 2 or 3 and the C6_Flag variable equals 1. The end and hence the duration of this first stay-at-home requirement is determined by finding the first date after the beginning of the requirement for which either C6_Stay at home requirements is at a level of 0 or 1 or the C6_Flag equals 0. Let the s_i and e_i denote the start and end of the lockdown for country *i*. Both variables are measured from the beginning of the 2020 calendar year. For example, a lockdown starting on March 15th 2020 and ending on March 29th 2020 would yield values of s_i and e_i equal to 74 and 88, respectively. We consider all periods *t* between the beginning and end of the lockdown for each country and we define the following six dummy variables Monday_t,…, Saturday_t , which are equal to 1 if the period corresponds to a Monday,…, Saturday, respectively, and otherwise these variables are equal to 0. With these definitions, for each country *i* with a lockdown period of at least 3 weeks we estimate the following linear model of workplace mobility m_{it} for country *i* in period *t*:

$$m_{it} = \alpha_i + \beta_i (t-s_i) + \pi_1 \text{Monday}_t + \pi_2 \text{Tuesday}_t + \pi_3 \text{Wednesday}_t + \pi_4 \text{Thursday}_t + \pi_5 \text{Friday}_t + \pi_6 \text{Saturday}_t + e_{it}, \text{ where } t \text{ in } s_i,..,e_i$$

In this linear model, α_i measures the expected mobility at the beginning of the lockdown, while β_i measures the change in mobility as the lockdown for country *i* is extended for an additional day. Hence, the latter coefficient yields a measure of fatigue in terms of the daily wear out effect of the lockdown for country i. Finally, e_{it} represents the error term of the model for country *i* in period *t*. This same methodology implemented at the country level is also applied separately to the analysis of US states.

We use country characteristics to explain differences in the mobility at the beginning of the lockdown, the fatigue or wear out effect and the mobility drop observed at the beginning of the lockdown. We rely on the following country characteristics, with their respective sources in parenthesis:

i. *wmbefore*: average **w**orkplace **m**obility observed between 4 and 10 days **before** the start of the lockdown (Google COVID-19 Community Mobility Reports).
ii. *sibefore*: average value of the **s**tringency **i**ndex observed between 4 and 10 days **before** the start of the lockdown (Oxford COVID-19 Government Response Tracker).
iii. *population*: country **population** (Google COVID-19 Community Mobility Reports)
iv. *area*: geographical **area** (squared kilometers, Google COVID-19 Community Mobility Reports).
v. *hdi*: **h**uman **d**evelopment **i**ndex (UNDP)
vi. *lifeexp*: **life exp**ectancy (years, UNDP)
vii. *gnipc*: **g**ross **n**ational **i**ncome **p**er **c**apita (UNDP)
viii. *expsch*: **exp**ected years of **sch**ooling (UNDP)
ix. *meansch*: **mean** years of **sch**ooling (UNDP)
x. *Gini*: **Gini** coefficient for income inequality (UNDP)

In order to select the explanatory variables to use in each model, we rely on a stepwise regression with both addition and removal of explanatory variables in each step according to a p-value of 0.3 for entry and removal. We obtain identical conclusions if we use instead a p-value of 0.1 for inclusion and removal. The estimation is implemented in the R statistical computing and graphics software using the ols_step_both_p function. Detailed results are presented below.

The first model we estimate explains differences across countries in their **m**obility at the **start** of the lockdown, as measured by the α_i coefficient, which for ease of exposition we refer to as *wmstart*. Results are shown in Table 1.

Table 1: Estimation results for a linear model of mobility at the start of the lockdown (*wmstart*) as a function of country characteristics.

Dependent Variable	wmstart		
Predictor	estimate	t statistic	p-value
intercept	89.337	2.680	0.010
sibefore	0.295	3.038	0.004
lifeexp	-1.734	-4.956	<0.001
Gini	-0.860	-2.834	0.007

R^2: 0.455, Adjusted R^2: 0.423; F-statistic: 13.94 on 3 and 50 degrees of freedom (n=54).

The second model considers differences in **fatigue** or the wear out effect of lockdowns, as measured by the α_i coefficient, which for ease of exposition we refer to as *fatigue*. We add to the list of country characteristics described above the estimated mobility at the beginning of the lockdown (*wmstart*). Table 2 shows the estimated model.

Table 2: Estimation results for a linear model of lockdown fatigue (*fatigue*) as a function of country characteristics.

Dependent Variable	fatigue		
Predictor	estimate	t statistic	p-value
intercept	0.702	2.392	0.020
wmstart	-0.012	-8.214	<0.001
wmbefore	-0.004	-2.446	0.018
lifeexp	-0.016	-3.605	0.001

R^2: 0.554, Adjusted R^2: 0.530; F-statistic: 22.8 on 3 and 55 degrees of freedom (n=59).

The third set of models considers differences in the initial mobility drop observed at the beginning of the lockdown, as measured by the difference between the baseline workplace mobility (*wmbefore*) and the mobility at the start of the lockdown (*wmstart*). We denote this initial mobility drop by *wmdrop,* where *wmdrop = wmbefore - wmstart*. Tables 3a and 3b show estimation results for regression models for *wmdrop* as a function of country characteristics, where the difference between the two tables is that Table 3b includes *wmbefore* as an additional regressor.

Table 3a: Estimation results for a linear model of the initial mobility drop (*wmdrop*) as a function of country characteristics.

Dependent Variable	wmdrop		
Predictor	estimate	t statistic	p-value
intercept	-38.565	-1.042	0.303
sibefore	-0.915	-8.479	<0.001
lifeexp	1.292	3.325	0.002
Gini	0.720	2.135	0.038

R^2: 0.662, Adjusted R^2: 0.642; F-statistic: 32.64 on 3 and 50 degrees of freedom (n=54).

Table 3b: Estimation results for a linear model of the initial mobility drop (*wmdrop*) as a function of country characteristics.

Dependent Variable	wmdrop		
Predictor	estimate	t statistic	p-value
intercept	-76.632	-2.203	0.032
wmbefore	0.750	3.641	<0.001
sibefore	-0.450	-2.812	0.007
lifeexp	1.623	4.510	<0.001
Gini	0.825	2.719	0.009

R^2: 0.734 , Adjusted R^2: 0.712; F-statistic: 33.79 on 4 and 49 degrees of freedom (n=54).

The fourth and final model considers differences in the baseline mobility before the lockdown (*wmbefore*) as a function of country characteristics. Table 4 shows the estimated model.

Table 4: Estimation results for a linear model of the baseline mobility before the lockdown (*wmbefore*) as a function of country characteristics.

Dependent Variable	wmbefore

Predictor	estimate	t statistic	p-value
intercept	26.472	3.105	0.003
sibefore	-0.617	-9.855	<0.001
hdi	-18.234	-1.731	0.089

R^2: 0.6374 , Adjusted R^2: 0.6245; F-statistic: 49.23 on 2 and 56 degrees of freedom (n=59).

Author Contributions

Both authors contributed equally to this research.

Materials and Correspondence

(* Information deleted for double blind review *)