Inequality, Lockdown, and COVID-19: Unequal Societies Struggle to Contain the Virus

ORIGINAL RESEARCH FROM THE CENTER ON INTERNATIONAL COOPERATION

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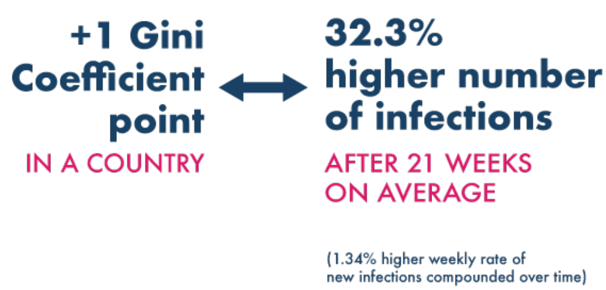
There is nothing equal about COVID-19. It is now well established that poor and underprivileged social groups have absorbed most of the pandemic's negative impact. However, the connection between COVID-19 and inequality might run even deeper. During the first wave of the COVID-19 pandemic, one additional point of the Gini coefficient correlated with a 1.34 percentage point higher rate of weekly new infections across countries. This difference in infection rates compounds like interest every week. This means that after twenty-one weeks of the pandemic, just one additional Gini point correlates with an approximately 1/3 higher overall number of cases in a country. More equal countries might enjoy an "equality dividend" that is associated with more shock resilience during the ongoing crisis.

What drives the virus spread?

Economic inequities on the pandemic's eve were already a daunting challenge.

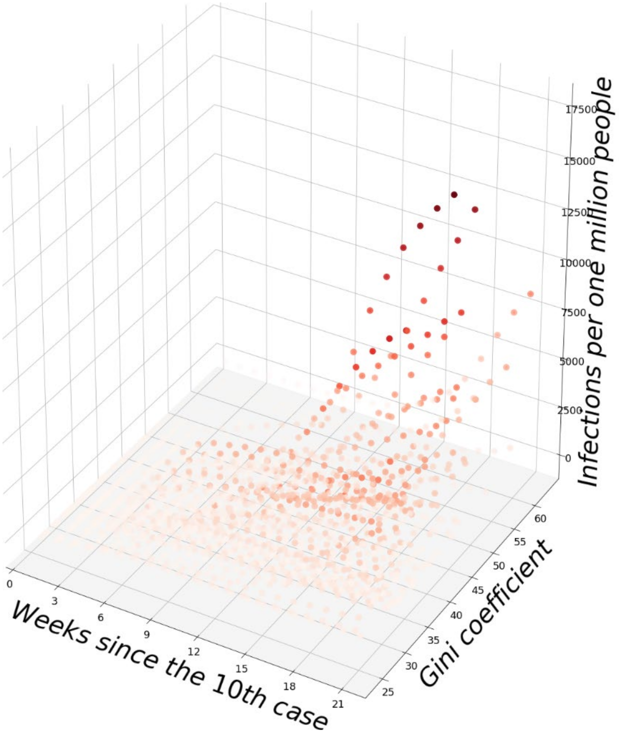
While after a decade of continuous economic growth poverty rates in developing countries were falling, the gap between the richest society members and the rest of kept growing, especially among developed countries. The global pandemic–a historic event of our generation–erased poverty reduction gains and threw into a sharp relief brewing socio-economic divides. In the US, the poorest were seven times more likely than the richest to work in industries that shut down in March 2020, a proportion likely to be similar in other rich nations. Women, who are the majority of workers in the service economy, were especially hard hit by closures and additional childcare commitments when 91% of children worldwide could not return to school. Minority group members more likely to work in the gig economy were suddenly dislocated by vanished demand in services. The ensuing crisis also became a lightning rod for protests and communal strife, particularly in fragile states.

Figure 1: Correlation between income inequality and the rate of weekly new cases per one million people



Against this backdrop, a question emerges whether the relation between COVID-19 and inequality might run in both directions, specifically whether pre-existing systemic inequities might link with higher infection rates. This article reviews patterns emerging from data on infection rates across countries to make a strong case supporting this hypothesis. To that end, econometric models based on seventy diverse countries were run, measuring the correlation between average weekly infections rates and a number of key characteristics. These include static features such as income inequality, government efficiency, urban population share, and the share of a population aged 65+, as well as time-varying factors such as lockdown stringency and satellite-measured geographic mobility trends across countries in each week since the tenth COVID-19 case was registered (*see the Technical Annex for details*).

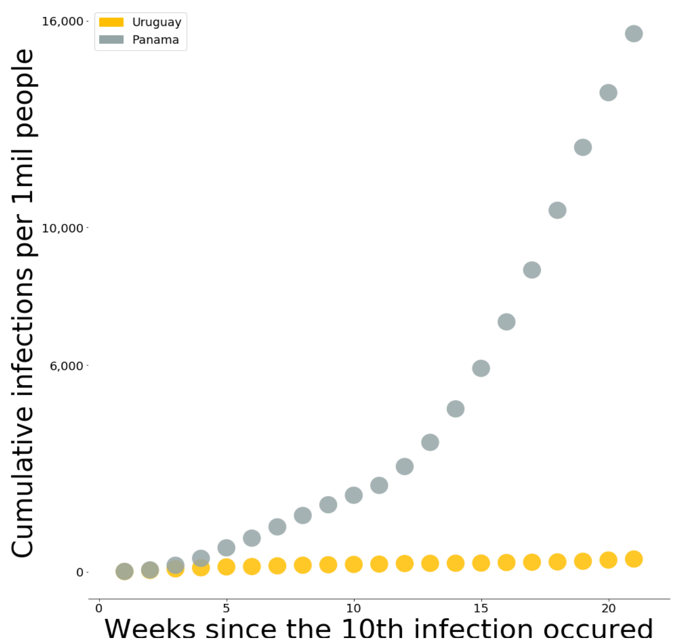
Figure 2: Infection rates over 21 weeks since the pandemic outbreak across the inequality spectrum measured by the Gini coefficient. More unequal countries edge up more strongly over time.



To verify the correlation between the Gini Coefficient and the rate of new weekly infections, seventy countries were tracked over twenty-one weeks since the outbreak of the pandemic (measured as surpassing ten infections). Twenty-one weeks corresponded with the period March - August 2020 for all of the analyzed countries and covered the pandemic's first wave, mostly contained by the end of the summer *(an expanded version of the model covering forty-two weeks is also discussed in the final part of the article).* It turns out that over the analyzed period, every additional Gini coefficient point was correlated with 1.34 percent points more weekly new infections per one million people across countries on average (Figures 1 and 2). This relatively small difference in infection rates compounds like interest every week. After just a few weeks a wedge between countries in terms of infection rates becomes visible as new infections lead to further ones in a chain reaction process. This effect can be described as an "inequality wedge." A compound accumulation calculation based on the model reveals that after twenty-one weeks, just one additional Gini point correlates with an approximately 1/3 (32.3%) higher overall number of cases in a country. If this correlation is causal, then for a country like the United Kingdom, which with a Gini Coefficient of 35 points is close to the world median, just one point less would have meant 75,000 fewer cases in late August, twenty-one weeks after the pandemic started there (as compared to 300,000 infections, which it had accrued by then). Higher Gini Coefficient score on the other hand would correlate with an even higher number.

For example, take two countries, Uruguay and Panama, which have comparable GDP per capita levels, population sizes, and climates but different levels of inequality. Uruguay's Gini index is 39.7 while Panama's is 49.2. For the first few weeks, infection rates look similar in both countries. However, a small wedge builds up over time, leading to an exponential jump in Panama. By the twenty-first week, Uruguay had 367 cumulative infections per one million people while Panama had 15,624, forty-three times more

Figure 3: Infections rates in Uruguay and Panama over 21 weeks since the outbreak

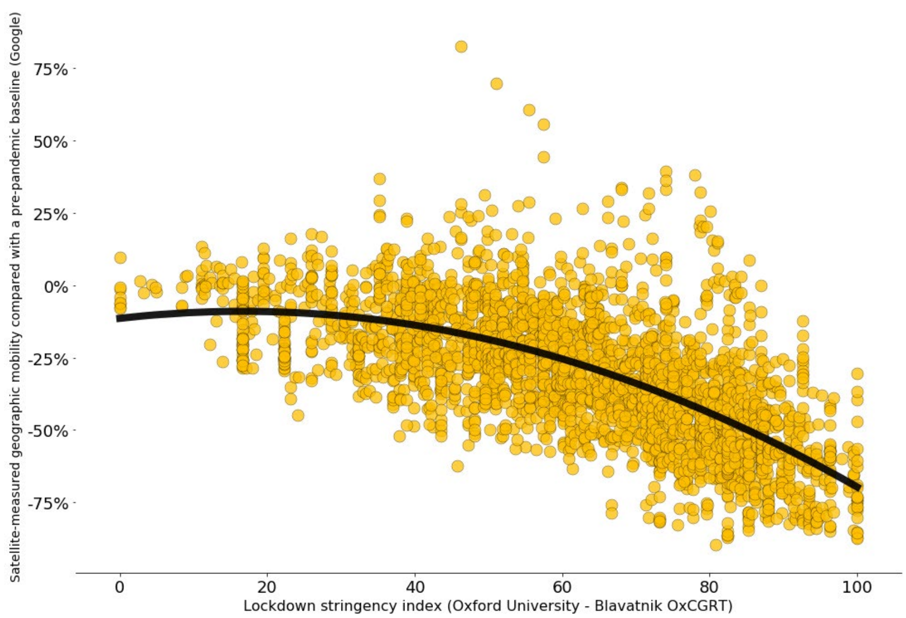


(Figure 3). This happened in spite of Uruguay having much softer lockdown rules throughout the whole analyzed period. The ten-point income inequality gap could account for a big part of that difference.

An array of other important features correlate with infection rates. One percentile point increase in the World Bank's government effectiveness measure (where the most effective government, Singapore, has a score of 100 and the least efficient one has 0) is linked with 0.63 percent point fewer new infections per one million people every week on average (which adds up to a significant constraint on virus spread over time). Urban population share in a country predictably leads to higher infection rates – for each additional percent point, there were 0.3 percent point more new average weekly infection per one million people across countries. Recent research by John Hopkins University suggests that this correlation might be driven by higher geographic mobility in a society and connectivity within urbanized areas rather than their population density, possibly compounded by more widespread testing in urban centers. Interestingly, the share of a society aged 65+ is negatively correlated with the infection rates. The exact reasons for this would have to be further analyzed. Older adults' higher risk of virus contraction might be potentially more than off-set by lower geographic mobility, better lockdown compliance, and lower employment in the service economy. At the same time, while contracted, SARS-CoV-2 virus presents a much higher risk of hospitalization and death to older adults. This correlation between age and COVID-19 mortality varies significantly across countries in a way that has not been fully explained but might be connected with cross-reactive immunity in countries affected by other types of Coronaviruses over recent years.

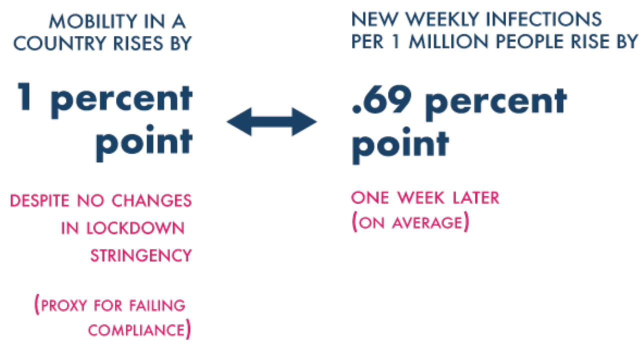
A strong correlation between lockdown stringency and infection rates also emerges from the data. Specifically, one more percent point of lockdown stringency *(measured by the Oxford Blavatnik index on a scale of 0 - 100*) is linked with 0.76 percent point fewer new weekly infections per one million people one week later. This is consistent with the medical findings on how much time it takes for the Novel Coronavirus to become symptomatic (5.1 days on average), leading to subsequent registering of a new infection. At the same time satellite data from the Google Mobility Report, measuring human traffic at transit stations compared with the pre-pandemic baseline, provides an insight into societal reaction to lockdown policies (Figure 4). It can also serve as a proxy for compliance with these policies and the price of lack thereof. Whenever geographic mobility in a society would increase by one percentage point while the lockdown stringency

Figure 4: Correlation between lockdown stringency and geographic mobility in a society (There is a circle for every analyzed country during each of the analyzed weeks)



index stayed constant (which might imply lower social compliance with existing rules), the rate of average weekly new infections would go up by 0.69 percent point one week later on average (Figure 5).

Figure 5: Average change in infection rates linked with geographic mobility rising despite existing lockdown rules



This is not to claim that inequality, government effectiveness, and geographic mobility on their own explain differences in COVID-19 response results between countries. There are many other factors at play such as: promptness of pandemic response, geographic characteristics, cultural features, or global human traffic exposure to list a few. The two models used for this analysis displayed R^2 metrics of 45% and 44% respectively, which is robust but suggests there are other aspects, which were not included in them, that also correlate with the outcome. Nevertheless, the models still identified a clear correlation between inequality and infection rates over time. This supports the hypothesis that the correlation might reflect a causal link running from the former to the latter.

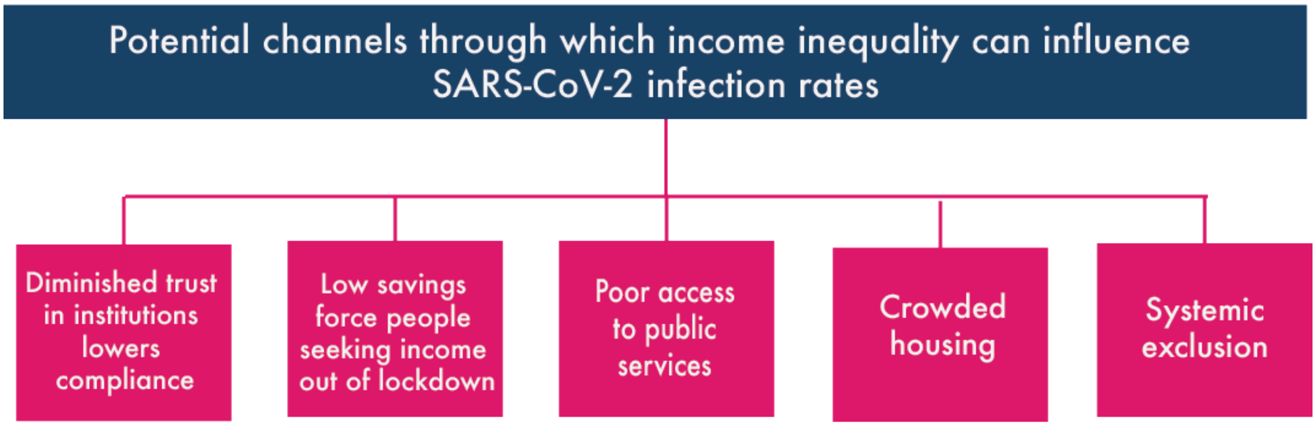
Data availability and quality remain a constraint. Infections and deaths from COVID-19 may be underreported in certain countries, with low-income economies more likely to lack capacity to identify and tally them up. Analysis of excess deaths suggests that indeed, this reporting gap appears to be inversely correlated with GDP per capita levels. As a way to address this, the models prepared for the article are based on a geographically balanced sample of seventy upper-middle income and high-income countries, where data quality might be better. However, the fact that variable Health Security Index denoting healthcare system capacity in the model– which implies better testing and virus tracing displayed a positive correlation with the infection rates across countries in the models indicates that some underreporting might still be present. Juxtaposing data on COVID-19 test rates and the Health Security Index score for the analyzed countries revealed a positive correlation between the two, reinforcing the impression that the accuracy of infection rates reported by countries still varies. Despite these constraints, an analysis of as many as 70 countries over a number of weeks allows for clear trends to emerge from the data.

The choice of the period March – August 2020 stems from the fact that by the end of the summer the first wave of the virus was largely contained in the analyzed countries, which allows for a stable comparison across them. The second wave of the pandemic, underway since the fall, overshadows the first one in its scale and is still far from over. For this reason, an expanded version of the model, encompassing forty-two rather than twenty-two weeks since pandemic outbreak in countries, is discussed separately in the last part of this article. Detailed presentation of all the models (a fixed-effects one for time-varying features and a regular regression for background characteristics) can be found in the Technical Annex.

How exactly can inequality drive spread of COVID-19?

It is important to understand the mechanisms by which inequality and exclusion can map onto more SARS-CoV-2 infections.

The Gini coefficient used for this analysis is a broad and potentially vague term. There are many ways income inequalities can correlate with differences in lived experience of communities that lead to virus transmission.



Unequal and exclusionary societies display lower trust levels, which can undermine compliance with government and medical expert guidelines. Economic deprivation undermines ability to save money by disadvantaged households, which limits ability to shelter in place before their members are forced out to seek income or relocate. Unequal societies also struggle to provide access to good public services to the lower rungs. Think about disparities between school districts in developed countries and better healthcare access in rich communities everywhere. This means there is less capacity in impoverished communities to cope with shocks such as a pandemic. A connection between lower income level and social status and crowded housing is also well established. Crowdedness lowers ability to isolate sick members of a household and compromises social bubbles. Finally, behavioral and cultural differences might accrue between social groups that result in lower chances for underprivileged communities to seek information and support during the pandemic. Each of these possibilities is discussed below. While it is challenging to present an ultimate proof for each of those mechanisms in light of noisy and incomplete data, the following evidence aims to make a compelling case that they might indeed explain part of the correlation between inequality and SARS-CoV-2 infections.

Figure 6: Correlation between trust in doctors and the Gini coefficient in analyzed countries

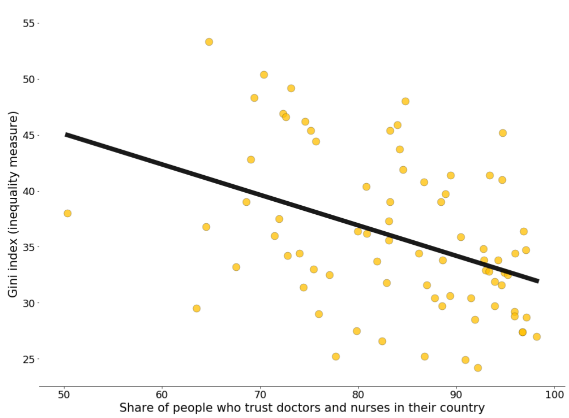
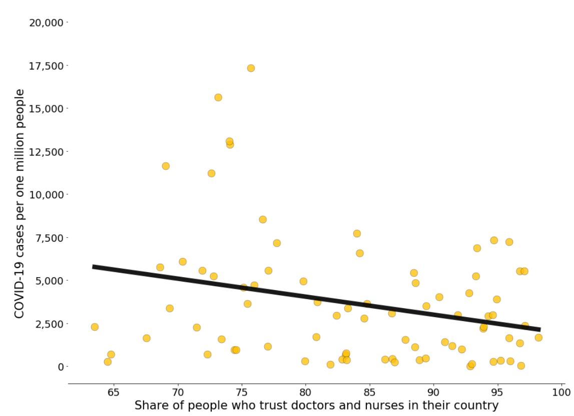


Figure 7: Correlation between trust in doctors and cumulative infection rates in analyzed countries 21 weeks after pandemic outbreak



In 2018, The Wellcome Global Monitor surveyed over 140,000 people from more than 140 countries whether they trust doctors and nurses in their country. The results are a good proxy for social trust as the survey specifically focuses on trust in professionals representing institutions directly linked to pandemic response **Figure 6** above reveals that there exists a trend across analyzed countries – stark income inequality means less trust in medical professionals, which can hurt compliance with pandemic guidelines. Consequently, if countries with lower trust levels suffer higher infection rates, it would support the argument that incomes inequalities might potentially drive them. **Figure 7** reveals that indeed, lower trust correlates with more infections. Recent reports on people disbelieving government communications during the pandemic in low-trust societies further strengthens this possibility.

The second potential channel, through which income inequality could aggravate infection rates, is the lack of financial buffers and resulting diminished economic ability to shelter in place for underprivileged communities. The precarious economic position of poor people in countries with widespread inequities can manifest itself in various ways. One of the seeming paradoxes of countries with deepening income inequality is that overall savings rates go up (since wealthy people invest higher shares of their earnings), while savings in poor parts of the society plummet. When a pandemic hits, the latter have less of a financial buffer that allow them to stay at home. People in lower income groups are also much more likely work gig economy jobs such as food delivery, which entail less job security and more risk to infection. As soon as savings dry up, they are forced to seek new employment, regardless of health risks. This is a problem in every country during the lockdown, but inequality compounds this effect.

It is challenging to find a proxy variable representing inequality's impact on financial safety of underprivileged communities. For example, national savings rate tends to go up when inequities deepen, hiding the fact that large parts of the society start saving less. Data on the size of informal economy tends to focus on developing countries, making it impossible to draw comparison across country groups representing various income levels. The variable that captures well purchasing power and the overall bargaining position of workers is the labor income as a share of GDP. In fact, it was recognized by the United Nations as the UN SDG Target 10.4.1, part of Goal #10: "Reduce inequality within and among countries." The indicator's main premise is that unequal societies reward labor less due to weaker bargaining position of the underprivileged social groups, for whom labor is the main form of income. At the same time, capital owners, who almost always come from wealthier parts of the society, collect a higher share of the GDP (labor and capital income sum up to 100% of a country's GDP).

Figure 8: Labor compensation share in the national income and the Gini coefficient in analyzed countries

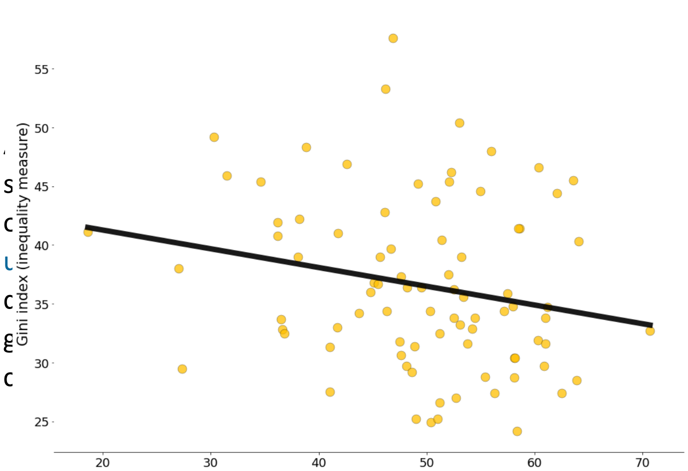
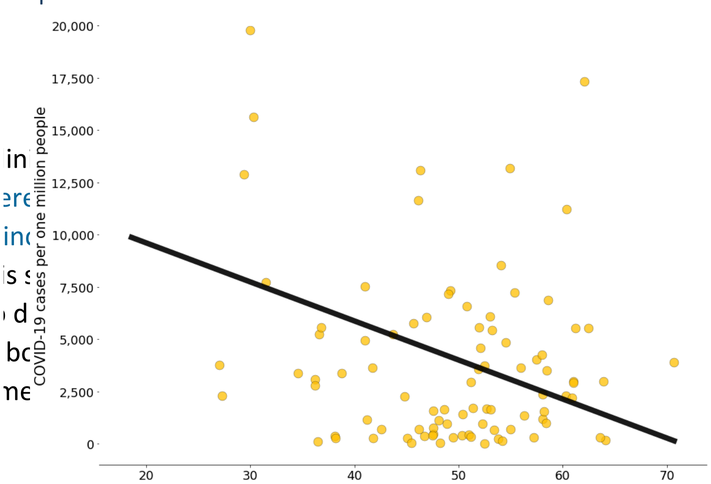


Figure 9: Labor compensation share in the national income and cumulative infection rates in analyzed countries t weeks after pandemic outbreak



Income inequality might also manifest itself through diminished access to public services, such as healthcare or education, as demonstrated time and again. In a similar fashion to the national savings level, oftentimes aggregate spending on the type of service goes up while the access in underprivileged social groups deteriorates. Variety of democracy offers a robust measure of inclusive access to public services by socio-economic groups. **Figure 10** shows that it is strongly linked with income inequality, while **Figure 11** shows that inclusive access to public services also weakly correlates with lower infection rates.

Figure 10: Inclusive access to public services and the Gini coefficient in analyzed countries

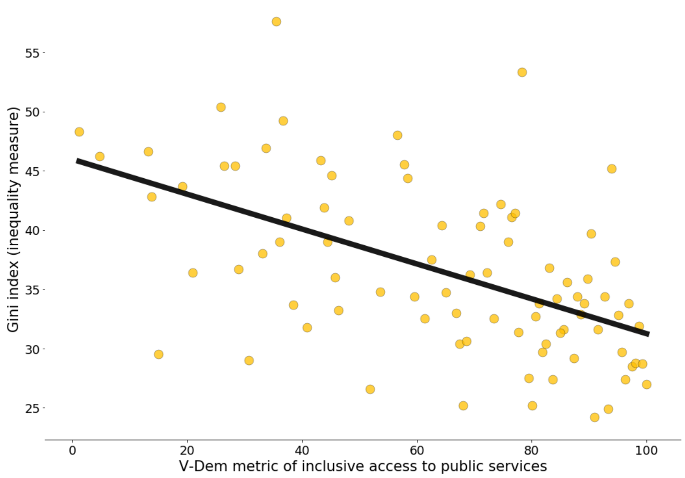
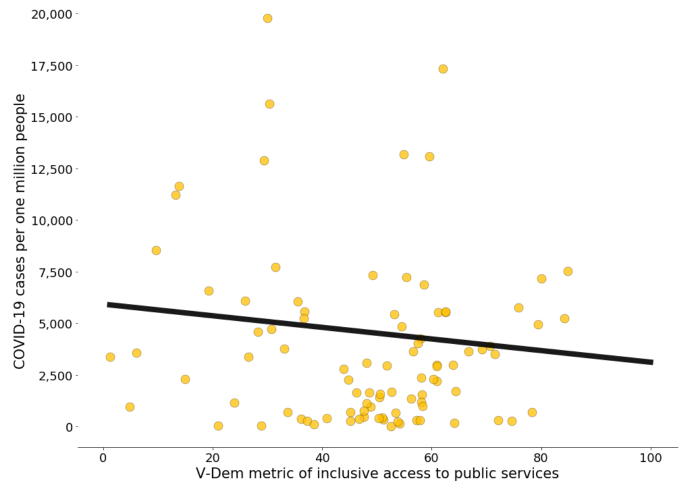
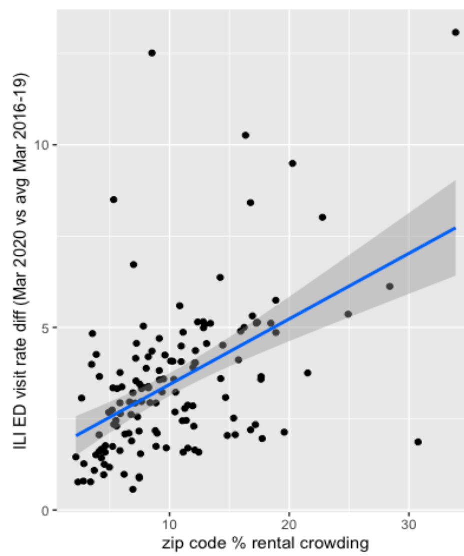


Figure 11: Inclusive access to public services and cumulative infection rates in analyzed countries 21 weeks after pandemic outbreak



Crowded housing conditions are strongly correlated with both income inequality and higher SARS-Cov-2 infection rates within a country. Worldwide, crowding is often a marker of poverty and social deprivation. Overcrowding also affects educational outcomes, mental, and physical health. It follows then over one billion people living in slums worldwide became particularly exposed to COVID-19. A study from November 2020 showed that 54 percent of COVID-19 tests collected among slum dwellers returned positive as opposed to only 16 percent in non-slum settings. While no database exists that would encompass enough countries for an econometric comparison, focused studies have confirmed the linkage for: China and Italy, United States, United Kingdom here and here, and many others. In New York City, an analysis by New York University epidemiologist Justin Feldman found a strong link between Emergency Department visits for "influenza-like symptoms" in March 2020 and overcrowded ZIP codes (**Figure 12**), consistent with a similar study at Columbia University.

Figure 12: Rental crowding and influenza-like symptoms ED visits in NYC in March 2020 compared to a baseline



Source: J. Feldman, Does COVID-19's toll reflect social inequality? Early evidence from NYC

When conceptualizing this linkage, it is important to distinguish between crowded housing and population density. The latter does not automatically map onto higher infection rates (as mentioned earlier in this article) if housing conditions are good, lockdown compliance is robust, and healthcare services are provided in an inclusive manner. There is no clear correlation between population density and COVID-19 deaths. In fact, better access to healthcare services might mean that death rates are actually lower in some densely populated areas.

Patterns of economic inequality lead to a systemic exclusion that creates informational and behavioral gaps between social groups. A study in the UK showed that these differences translate to gaps in health seeking behavior, experiences of healthcare, and ultimately health outcomes during the COVID-19 pandemic. The information gap driven by economic and social inequities is compounded by the digital divide. Every important aspect of life: work, education, healthcare, consumption, among others depend now on the access to the internet and resources found there. This Education Week survey found that 64% of American teachers in schools with a large number of low-income students see their pupils face technology limitations, compared to 21% of students in schools with a small number of low-income students. Meanwhile, McKinsey found this dynamic to also have a strong racial and ethnic lens. Lastly, this study in the Netherlands found that the elderly, people without higher education, and those with low-paying jobs–all at higher risk of being infected by SARS-CoV-2–were less likely to benefit from internet-based informational resources on COVID-19.

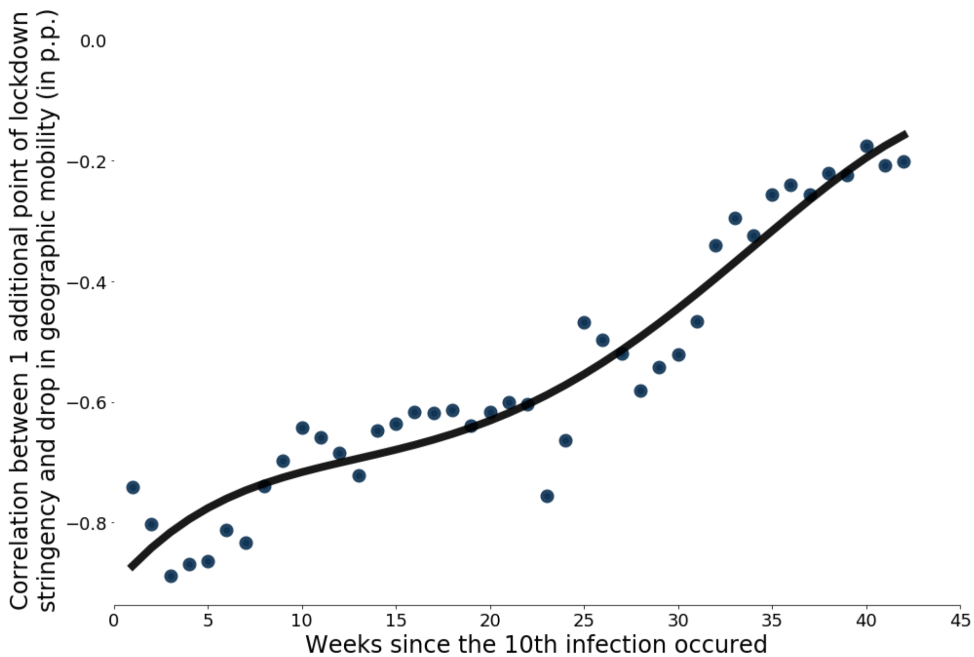
Economic inequality is proven to worsen health-related issues. These pre-existing conditions leave underprivileged communities vulnerable to SARS-CoV-2 infections and at a higher risk of dying from COVID-19. Poverty-induced stress and the experience of childhood deprivation are imprinted in a person's eating habits. A study of 31 OECD countries found that around 20 percent of variation in weight in a society is driven by income inequality, with a 1-point increase in the Gini coefficient corresponding to a 1 percentage point increase in the obesity rate among women and a 0.82 percentage point increase among men. Analogous results were observed in Latin America. A study in Ghana found that the correlation might reverse in the poorest countries and then alters direction as a society becomes richer. Obesity is linked to non-communicable diseases, most notably type-2 diabetes, heart attacks and other cardiovascular disease, gallbladder disease, and cancer. Change in the Gini coefficient explains around 80 percent of change in diabetes mortality rate among developed countries of similar income. These conditions create an additional hazard during the pandemic. This study in Nature delineated how a higher risk of obesity and diabetes makes underprivileged communities more vulnerable during the COVID-19 pandemic. An obesity problem might be explaining partially higher death rates during the pandemic in some countries, such as the United States and United Kingdom. The problem has both an income inequality and an identity-based exclusion dimension, with underprivileged racial and ethnic groups being most at risk. All those differences are expressed in not only in how fast the virus is spreading and killing people, but also in how slowly it is receding. For example, for the United Kingdom the fall in COVID-19 cases is slower in their poor regions.

Policy implications

A prompt government response to the COVID-19 pandemic has been a decisive factor in terms of curbing the spread of the virus in 2020 during the early days of the pandemic. However, as the weeks and months passed and the crisis response turned from a sprint into a marathon, the underlying socio-economic conditions inevitably came to the forefront and became the key correlates of infection rates.

By December 2020, approximately four million new infections were being recorded every single day among the seventy analyzed countries, which dwarfs the dynamics from March until the end of August. For this reason, and because this new pandemic wave has not yet stabilized, a twenty-one week model was used as the main source of insights for this article. However, when models used for this analysis are applied to the expanded dataset covering forty-two weeks, the results are remarkably consistent. One important difference is the weakening correlation between lockdown stringency and satellite-measured changes in geographic mobility at transit stations. In fact, as **Figure 13** reveals, that connection has been consistently weakening across countries as weeks passed. The exact reasons for this phenomenon can be diverse and should be further analyzed. One possible explanation is that compliance with lockdown rules has been worsening. However, another reason for the correlation to weaken could be that procedures have been developed to travel and commute in a safe manner. Lockdowns might have also become more tailored as infection clusters are now more easily detectable. To the extent that this dynamic represents falling social compliance rates and diminishing relevance of lockdown policies over time, it implies that the impact of underlying socio-economic conditions, including economic inequities, grows when a crisis becomes protracted.

Figure 13: Correlation between one additional point of lockdown stringency and a drop in geographic mobility. The correlation weakens as weeks progress, which can be connected with lower compliance.



In the short-term, this lesson from the pandemic dynamics in 2020 can inform the vaccine rollout strategy in 2021. The same underprivileged communities that have been hotspots of SARS-CoV-2 infections can become a fertile ground for the virus to develop new strains before enough people are vaccinated. In fact, inequality in vaccine rollout, both within countries and between them, already display a strong income-related pattern, which suggests an existence in the a risk of repeating the mistake of letting inequities undermine the pandemic response.

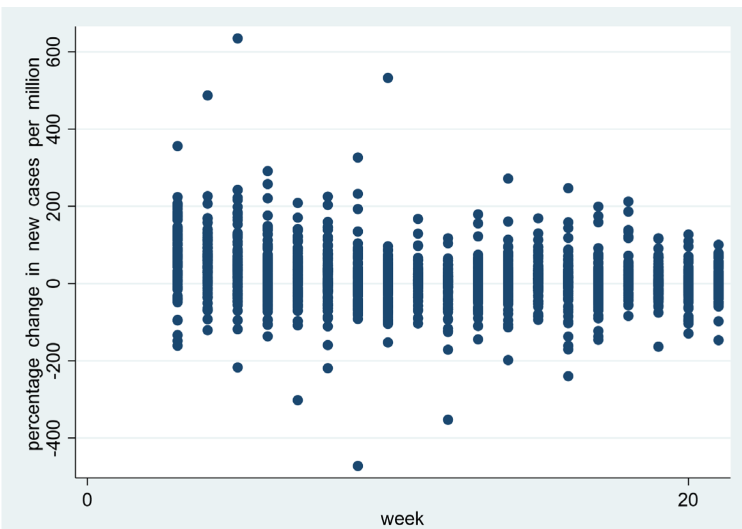
In the long term, equality and inclusion, already core values of the UN Sustainable Development Goals agenda, should also become the center of a broader strategy of building resilience against future shocks. This goes beyond the fragile state context, in which shock resilience is usually discussed, and applies to both developing and developed countries. Apparent diminishing social reaction to lockdown restrictions shows that compliance by force has a shelf life. Studies now affirm that regions within countries, such as in Italy that have higher civic capital and social trust measures display greater and more enduring lockdown compliance levels from early on, which is decisive in halting the virus' spread. **In this context, a policy commitment to socio-economic equality and inclusion can be perceived as part of a social contract and a genuine investment in a nation's development and a way to build back better after the pandemic.**

Technical annex

70 Countries included in the study:

Argentina, Australia, Austria, Belarus, Belgium, Bosnia and Herzegovina, Brazil, Bulgaria, Canada, Chile, Colombia, Costa Rica, Croatia, Czechia, Denmark, Dominican Republic, Ecuador, Estonia, Fiji, Finland, France, Georgia, Germany, Greece, Guatemala, Hungary, Indonesia, Iraq, Ireland, Israel, Italy, Japan, Jordan, Kazakhstan, Lebanon, Lithuania, Malaysia, Malta, Mauritius, Mexico, Namibia, Netherlands, New Zealand, Norway, Panama, Paraguay, Peru, Poland, Portugal, Romania, Russia, Saudi Arabia, Serbia, Singapore, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, Trinidad and Tobago, Turkey, Qatar, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela

Distribution of the dependent variable observations over time is stationary (relevant for the panel data models 1a and 2a).



Model 1a. Fixed-effects model measuring the correlation with time-varying variables over 21 weeks after the 10th case

Percentage change in weekly new cases per million people	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
L1.cases_per_million	-.003	.001	-2.42	.018	-.005	0	**
L1. Percentage change in weekly new cases per million people	.202	.043	4.73	0	.117	.288	***
L1.Stringency Index	-.762	.229	-3.32	.001	-1.219	-.304	***
L1.Transit_stations_mobility	.692	.21	3.30	.002	.274	1.11	***
2.week	0	.	.	.	.	.	
3.week	-32.684	15.574	-2.10	.04	-63.753	-1.616	**
4.week	-27.33	17.121	-1.60	.115	-61.485	6.826	
5.week	-14.777	18.07	-0.82	.416	-50.825	21.27	
6.week	-30.462	16.683	-1.83	.072	-63.745	2.82	*
7.week	-45.438	16.35	-2.78	.007	-78.055	-12.822	***

8.week	-42.462	17.354	-2.45	.017	-77.082	-7.842	**
9.week	-49.083	17.452	-2.81	.006	-83.898	-14.268	***
10.week	-54.487	17.742	-3.07	.003	-89.881	-19.092	***
11.week	-50.819	16.994	-2.99	.004	-84.72	-16.917	***
12.week	-74.466	20.515	-3.63	.001	-115.393	-33.54	***
13.week	-60.496	19.819	-3.05	.003	-100.034	-20.959	***
14.week	-56.151	18.842	-2.98	.004	-93.741	-18.562	***
15.week	-59.646	18.271	-3.26	.002	-96.096	-23.196	***
16.week	-71.808	19.947	-3.60	.001	-111.6	-32.015	***
17.week	-66.493	17.987	-3.70	0	-102.377	-30.61	***
18.week	-65.563	18.395	-3.56	.001	-102.26	-28.866	***
19.week	-70.284	18.658	-3.77	0	-107.506	-33.063	***
20.week	-71.854	19.817	-3.63	.001	-111.388	-32.32	***
21.week	-62.86	17.948	-3.50	.001	-98.666	-27.054	***
Constant	147.704	17.186	8.59	0	113.419	181.99	***

Mean dependent var	21.053	SD dependent var	74.046
R-squared	0.450	Number of obs	1316.000
F-test	43.392	Prob > F	0.000
Akaike crit. (AIC)	14246.746	Bayesian crit. (BIC)	14365.940

**** p<.01, ** p<.05, * p<.1*

Model 1b. Regular regression model measuring the correlation with time-invariant variables (21 weeks after the 10th case)

Percentage change in weekly new cases per million people	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
L1.cases_per_million	.352	.036	9.92	0	.281	.423	***
L1. Percentage change in weekly new cases per million people	-.003	.001	-3.11	.003	-.005	-.001	***
L1.Stringency Index	-.597	.161	-3.72	0	-.918	-.277	***
L1.Transit_stations_mobility	.424	.14	3.03	.003	.145	.704	***
government_effecti~t	-.628	.178	-3.53	.001	-.983	-.273	***
gini	1.337	.221	6.04	0	.896	1.779	***
urban_population_s~e	.298	.112	2.66	.01	.075	.522	***
aged_65_older	-.781	.378	-2.07	.042	-1.534	-.027	**
gdp_per_capita	0	0	1.90	.062	0	.001	*
education_upper_se~y	.102	.147	0.69	.491	-.192	.396	
health_security_in~x	.688	.203	3.40	.001	.284	1.092	***

Mean dependent var	21.053	SD dependent var	74.046
R-squared	0.439	Number of obs	1316.000
F-test	97.627	Prob > F	0.000
Akaike crit. (AIC)	14428.240	Bayesian crit. (BIC)	14485.245

**** p<.01, ** p<.05, * p<.1*

Model 2a. Fixed-effects model measuring the correlation with time-varying variables over 42 weeks after the 10th case

Percentage change in weekly new cases per million people	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
L1.cases_per_million	-.001	0	-4.64	0	-.001	-.001	***
L1. Percentage change in weekly new cases per million people	.231	.047	4.89	0	.137	.325	***
L1.Stringency Index	-.752	.138	-5.45	0	-1.027	-.477	***
L1.Transit_stations_mobility	.376	.091	4.12	0	.194	.558	***
3.week	-37.809	15.707	-2.41	.019	-69.143	-6.474	**
4.week	-34.726	16.861	-2.06	.043	-68.362	-1.09	**
5.week	-23.45	17.748	-1.32	.191	-58.857	11.957	
6.week	-40.112	16.24	-2.47	.016	-72.511	-7.714	**
7.week	-54.496	16.254	-3.35	.001	-86.921	-22.071	***
8.week	-50.865	16.48	-3.09	.003	-83.742	-17.988	***
9.week	-57.684	16.51	-3.49	.001	-90.621	-24.747	***
10.week	-62.438	16.498	-3.78	0	-95.35	-29.526	***
11.week	-57.893	15.834	-3.66	0	-89.481	-26.306	***
12.week	-81.505	19.004	-4.29	0	-119.416	-43.594	***
13.week	-66.223	18.683	-3.54	.001	-103.496	-28.951	***
14.week	-61.376	16.924	-3.63	.001	-95.14	-27.613	***
15.week	-64.828	16.13	-4.02	0	-97.006	-32.65	***
16.week	-77.91	19.287	-4.04	0	-116.386	-39.434	***
17.week	-72.007	16.042	-4.49	0	-104.01	-40.005	***
18.week	-70.056	16.509	-4.24	0	-102.99	-37.122	***
19.week	-74.74	16.729	-4.47	0	-108.113	-41.367	***
20.week	-76.158	17.727	-4.30	0	-111.523	-40.792	***
21.week	-67.139	15.577	-4.31	0	-98.215	-36.063	***
22.week	-75.066	16.312	-4.60	0	-107.608	-42.525	***
23.week	-63.031	14.119	-4.46	0	-91.197	-34.865	***
24.week	-72.984	15.576	-4.69	0	-104.057	-41.911	***
25.week	-76.246	16.034	-4.76	0	-108.234	-44.259	***
26.week	-72.73	15.37	-4.73	0	-103.392	-42.069	***
27.week	-75.304	15.677	-4.80	0	-106.579	-44.029	***
28.week	-74.848	16.061	-4.66	0	-106.889	-42.807	***
29.week	-65.867	14.806	-4.45	0	-95.403	-36.331	***
30.week	-76.314	15.259	-5.00	0	-106.756	-45.872	***
31.week	-74.141	15.387	-4.82	0	-104.838	-43.445	***
32.week	-74.221	16.327	-4.55	0	-106.793	-41.65	***
33.week	-61.354	14.624	-4.20	0	-90.527	-32.18	***
34.week	-69.744	15.922	-4.38	0	-101.509	-37.98	***
35.week	-62.114	14.716	-4.22	0	-91.471	-32.757	***
36.week	-65.143	15.316	-4.25	0	-95.697	-34.59	***
37.week	-69.344	15.674	-4.42	0	-100.613	-38.074	***
38.week	-63.442	15.119	-4.20	0	-93.604	-33.28	***
39.week	-65.587	15.474	-4.24	0	-96.457	-34.717	***
40.week	-59.291	15.561	-3.81	0	-90.334	-28.248	***
41.week	-67.89	15.566	-4.36	0	-98.943	-36.837	***
42.week	-65.185	16.005	-4.07	0	-97.114	-33.256	***
Constant	136.776	18.236	7.50	0	100.396	173.157	***
Mean dependent var		15.068	SD dependent var			57.129	

R-squared	0.382	Number of obs	2773.000
F-test	56.656	Prob > F	0.000
Akaike crit. (AIC)	29006.800	Bayesian crit. (BIC)	29267.618

**** p<.01, ** p<.05, * p<.1*

Model 2b. Regular regression model measuring the correlation with time-invariant variables (42 weeks after the 10th case)

percentage_change_~p	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
L.percentage_chang~p	.374	.039	9.51	0	.295	.452	***
L.cases_per_million	-.001	0	-5.38	0	-.001	0	***
L.StringencyIndex	-.443	.092	-4.82	0	-.626	-.259	***
L.transit_stations~_	.259	.064	4.07	0	.132	.386	***
government_effecti~t	-.31	.107	-2.91	.005	-.523	-.097	***
gini	.615	.134	4.58	0	.347	.882	***
urban_population_s~e	.236	.082	2.89	.005	.073	.399	***
aged_65_older	-.416	.217	-1.92	.059	-.849	.017	*
gdp_per_capita	0	0	0.42	.675	0	0	
education_upper_se~y	.077	.078	0.98	.328	-.079	.234	
health_security_in~x	.504	.132	3.81	0	.24	.767	***

Mean dependent var	15.068	SD dependent var	57.129
R-squared	0.359	Number of obs	2773.000
F-test	96.439	Prob > F	0.000
Akaike crit. (AIC)	29280.294	Bayesian crit. (BIC)	29345.499

**** p<.01, ** p<.05, * p<.1*

Data Sources

- Infection rates: John Hopkins University Coronavirus Resource Center (https://coronavirus.jhu.edu/map.html)
- Lockdown Stringency Index: Oxford University | Blavatnik School of Government COVID-19 Government Response Tracker (https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker)
- Geographic mobility data at transit stations: Google Mobility Report (https://www.google.com/covid19/mobility/)
- Global Health Security Index: GHS Index (https://www.ghsindex.org/)
- GDP PC, Age structure, Education level, Government effectiveness: The World Bank (https://data.worldbank.org/)

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