What Does Cross-Country Data Speak about COVID-19?[1]

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This version: 22 August 2020

Abstract

This paper studies why there has been a large variation across countries on the COVID-19 confirmed cases and deaths. Taking into account the possibility of underreporting, we still find some robust patterns in how the reported infections and deaths are linked with some predetermined country characteristics. For both infection and death, average income, population density and income inequality are the three most important risk factors; government effectiveness, temperature and hospital beds are the three most important protective factors. All else being equal, a 100% increase in GDP per capita is associated with a 104% increase in infections per million people. Enhancing the government effectiveness from a level of Italy to that of South Korea, would reduce infections by more than 70%. Doubling population density may cause a 21% increase in deaths per million people. Doubling hospital beds may reduce deaths by 73%. An 8% more unequal income distribution from the global average is associated with 40% more infections and 25% more deaths per million population. A country with 11 degrees Celsius higher from the global average may expect 52% lower infections and 75% lower deaths per million population. Using a stochastic frontier approach, we provide a global ranking for 100 countries from 4 January to 15 August 2020, on their overall policy effectiveness in fighting against COVID-19 caused infections and deaths.

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1. Introduction

On 11 March 2020 WHO Director General characterized COVID-19 as a pandemic. Globally, by the 15 August 2020, there have been more than 20 million confirmed cases of COVID-19, including 750,000 deaths, reported to WHO. Under the big picture of global pandemic, there is also a substantial variation in infections and deaths across different countries. The United States, for example, has lost more than 170,000 lives due to COVID-19, far more than any other country. Vietnam, a country with a population size about one-third of the US, on the other hand, only recently reported 25 COVID-19 death cases so far.

The increasing spread of the coronavirus across countries has prompted many governments to introduce unprecedented public policies to contain the pandemic. "Everyone wants to know how well their country is tackling coronavirus, compared with others", as pointed out in one of the recent BBC reality checks[2]. However, the same report was in fact highlighted under the title "Why are international comparisons difficult?"

There are two broad issues to consider. First, it does not make sense to compare two sets of numbers directly if all the other factors surrounding the spread of the disease are different. What is underneath the huge variation of the pandemic could be the huge heterogeneity in some important risk and protective factors of the disease[3]. Second, the reported numbers for infection and death themselves could be dubious due to underreporting, arising from a lack of testing capacity, variable testing regimes or reporting guidelines, and the presence of asymptomatic infections[4]. This paper aims to fill in the big gap between what people demand to know and what the existing cross-country data can tell, by addressing these two challenges.

In Section 2, we start with how the global pandemic has distributed heterogeneously across countries, by documenting the patterns and statistics for a set of normalized measures by country. This set includes cumulative and daily cases for infection and death per million people, and the case fatality rate (CFR), from 4 January to 15 August. A raw global ranking based on these measures highlights an interesting fact: best and worst countries in the ranking are vastly different in many aspects. This motivates our cross-country regression analyses.

[2] "Coronavirus: Why are international comparisons difficult?" by Chris Morris and Anthony Reuben.
[3] While epidemiologists have been using the SIR models to analyze and forecast the course of the COVID-19 within a country, there are a number of heterogeneities that are important in practice but are not incorporated in the baseline versions of SIR models (Avery, et al, 2020). The importance of heterogeneity calls social scientists to advance the relevant literature using alternative approaches.
[4] For example, here are two influential media reports for underreporting concerns on infection, "Antibody surveys suggesting vast undercount of coronavirus infections may be unreliable", and on death, "Global coronavirus death toll could be 60% higher than reported".

Section 3 examines to what extent the substantial variations documented in Section 2 could be explained by a set of predetermined country characteristics. This includes demographic conditions, geographic conditions, economic conditions, global interdependency, healthcare conditions and public governance. We hypothesize that on top of the public policies containing the spread of the disease, these predetermined country characteristics could be the fundamental factors surrounding the spread of the disease. Although we are not able to directly address the underreporting concerns, from our regression analyses we do find some interesting evidences that are consistent with the conjecture of massive underreporting.

Then we ask the following question: conditional on the presence of underreporting, is there still anything that we can say about COVID-19 with confidence from cross-country data? We find there does exist a set of explanatory variables that are robustly significant under different model specifications, across different subsamples, and with reasonable adjustment for the reported infection and death numbers. All else being equal, a country with higher GDP per capita, higher population density, larger income Gini coefficient, fewer hospital beds, lower temperature and lower government effectiveness, tends to have more infections and deaths. For example, all else being equal, a 100% increase in GDP per capita is associated with a 104% increase in infections per million people. Enhancing the government effectiveness from a level of Italy to that of South Korea, would reduce infections by more than 70%. Doubling population density may cause a 21% increase in deaths per million people. Doubling hospital beds may reduce deaths by 73%. An 8% more unequal income distribution from the global average is associated with 40% more infections and 25% more deaths per million population. A country with 11 degrees Celsius higher from the global average may expect 52% lower infections and 75% lower deaths per million population.

Our cross-country regression model provides a useful statistical device. It shows on average how the set of predetermined country characteristics would predict the COVID-19 infections and deaths for each country. As the actual infections and deaths are the outcome of both predetermined country characteristics and the pandemic policies, if we use the global average as a benchmark, the gap between the actual and the predicted numbers, then offers an indirect and holistic inference on how effective each country has been dealing with the COVID-19 relative to others. Based on this rationale, and using a stochastic frontier approach, we provide a global ranking with efficiency scores in Section 4. We find that for some countries, such as China and the US, their rankings do vary a lot over the pandemic course; and for other countries, such as Singapore, their rankings do vary by infections or by deaths. We also find some countries who have been consistently exceptionally better or worse than the global average, even after controlling for a large set of predetermined country characteristics. Subject to the potential limitations, we discuss what useful messages are likely to emerge from our cross-country comparisons in Section 5.

2. Data and Patterns: Infections and Deaths

Various sources have been tracking the confirmed infections and deaths by country over time. In this paper we use the data from WHO, which are officially reported by the Center for Disease Control and Prevention or Ministry of Health or equivalent of each country. In particular, we collect number of infections and deaths of COVID-19 from 4 January to 15 August 2020 on daily basis for 100 countries, which have complete information on all the independent variables in our regression analyses[5].

Since its first emergence in late 2019, COVID-19 has rapidly spread to most of the countries in the world. To provide an overview of the global situation, we first display the time series plots of global cumulative and daily cases in Figure 1a and 1b, respectively. An exponential form of global cumulative infections and deaths is revealed in Figure 1a. Specifically, the curves were relatively flat in January and February. They started increasing rapidly around the declaration of global pandemic by WHO on 11 March. The fact that early to middle March is the global outbreak point is also revealed in Figure 1b by the sharp increase of the daily cases. After April, daily infections continue growing, while daily deaths show a decreasing trend. Starting from June, the number of daily infections rises quickly again although daily death cases stay relatively stable. During the last month of our sample period, on average, the coronavirus has infected more than 200,000 people and killed more than 5,000 people worldwide every day, suggesting that the global transmission of the virus has not been under control.

<Figure 1a and 1b here>

Next, we compare the COVID-19 outbreak across countries by plotting daily infections per million people for four representative countries, Vietnam, China, the US and Luxembourg, in Figure 2. We first find that the scale of the COVID-19 outbreak varies substantially among countries. Vietnam has the lightest outbreak with its highest daily infections of 0.5 per million people, while that of China is more than 20 times higher. [6] However, the pandemic outbreak is markedly severer in the US and Luxembourg as their maximal daily infections are around 225 and 1,200, respectively. So, why are the infections so different, even after normalized by population size?

<Figure 2 here>

Moreover, countries have various patterns of COVID-19 transmission. Luxembourg reached its first peak less than a month since the first reported case in early March. In contrast, the first confirmed case in the US was reported in late January and the number of infections only started increasing quickly two months later. Eventually, the number of daily infections in the US reached

[5] The data are available at: https://covid19.who.int/?gclid=EAIaIQobChMI4pHX-I-s6gIVmAVyCh3_1QSzEAAYASAAEgIKFPD_BwE

[6] On February 14, Hubei officials changed their diagnostic criteria, resulting in a spike in reported cases.

its first peak in late April. Finally, except China, the other three countries all experience a second wave of infection in late July. For both Vietnam, the often-cited role model of dealing with the pandemic, and the US, the most criticized developed country in dealing with the pandemic, the second wave are even severer than the first one in terms of infection rate. Once again, this suggests that the global pandemic has been far from a quick end.

<Table 1 here>

To better examine the heterogeneity of COVID-19 outbreak across countries, we provide the summary statistics and a raw global ranking for cumulative infections and cumulative deaths per million population, and the CFR in Table 1. Firstly, we observe substantial variation between minimum and maximum values of these variables. The minimal cumulative infection is 3 per million people so far, while its maximum is 41,174. This is also reflected by the global ranking where countries in the best 10 list have tremendously lower infections and deaths compared to the worst 10 countries. Similarly, we obtain large standard deviations for these three variables, again suggesting that countries are affected by the COVID-19 to a very different extent.

Next, a direct comparison between the best and worst 10 countries highlights that these are two very different groups. Most of the worst 10 countries are developed countries or large emerging economies, while most of the best 10 countries are developing economies. For example, the UK, with GDP per capita of 42,943 USD in 2018, is ranked the worst 10 countries for its cumulative death and CFR, while Laos, whose GDP per capita is 2,542 USD, achieves the best place in all three rankings. Why the COVID-19 seems to be severer within countries that are economically more developed? One possible explanation is that economic activities are much higher in developed countries and hence, this causes greater transmission of virus. Alternatively, a lower average income is usually associated with poorer healthcare conditions and public governance, which may lead to more underreporting and hence fewer reported infections and deaths.

Another interesting observation is that, the geographical location may also affect infections and deaths as the worst 10 countries are mainly from Europe and Americas, while most of the best 10 countries are from Africa and South East Asia. Finally, it is also worthwhile to point out that, although there is a large overlap in the list of worst and best countries for infection and death, some countries with very bad infection rates may have relatively low death rates. For example, Qatar has the world's worst infections per million people but is among the 10 best countries for CFR.

All these comparisons and observations suggest that, it is important to control the large heterogeneity in other factors that may affect the infection and death in a statistical way, in order to provide a fair global ranking on the efficiency of pandemic policies. This motivates our regression analyses in Section 3.

3. Cross-country regression

3.1. Empirical Specification

Since different countries were hit by the pandemic on different time points, we put them in same phases of the pandemic by considering the following regression:

(1) $$y_{i,t} = \beta_1 X_i + \beta_2 Z_{i,t} + f\,(Days_{i,t}) + \varepsilon_{i,t}.$$

Here $y_{i,t}$ represents the number of cumulative confirmed infections or deaths per million people, for country i. Different from a usual panel data regression, here t represents days since the first confirmed infection or death was reported in a country, instead of a calendar date.

X_i denotes a set of predetermined variables that may affect how vulnerable a country is inherently to COVID-19. $Z_{i,t}$ refers to additional time-varying control variables that may affect the reported infections or deaths besides X_i. As the outbreak of COVID-19 took place in different countries on different dates, a common time trend, $Days_{i,t}$, days since the first confirmed infection or death was reported in country i on date t, is included in the regression in a nonlinear form $f\,(\cdot)$ to control for the impact of different outbreak dates on infections or deaths.

The time-invariant coefficients β_1 and β_2 capture the average effects of X_i and $Z_{i,t}$ on $y_{i,t}$ over time. However, depending on the epidemiology of the disease, the same set of variables may have different predicting power to the pandemic over time. In addition, some explanatory variables which are essential determinants in an early stage may become less relevant at a late stage, or the other way round. To allow for time-varying β_1 and β_2, we also run regression of (1) using subsamples made of different weeks over the pandemic course.

Regression (1) does not explicitly include any COVID-19 pandemic policies that countries have been adopting. Although understanding the causal effect of specific policies is crucially important, it is not the goal of this paper. Instead, here we take a reduced-form approach to assess the relative effectiveness of the pandemic policies as a whole for each country. Denote such policies as $W_{i,t}$. The infections and deaths in a country $y_{i,t}$, should be affected by $W_{i,t}$, on top of X_i and $Z_{i,t}$, i.e.,

(2) $$y_{i,t} = \alpha_1 X_i + \alpha_2 Z_{i,t} + \alpha_3 W_{i,t} + g\,(Days_{i,t}) + \eta_{i,t}.$$

However, such containment policies, by definition, must depend on the situation of the pandemic itself and would be endogenous if they were included in our regressions. Furthermore, as pointed out in Angeli and Montefusco (2020), the containment policies are highly dependent on initial country specific characteristics. That is, $W_{i,t}$ itself may also depend on X_i and $Z_{i,t}$, in addition to $y_{i,t}$. which implies that we could write $W_{i,t}$ as,

(3) $$W_{i,t} = \pi_1 X_i + \pi_2 Z_{i,t} + \pi_3\, y_{i,t} + \xi_{i,t}$$

Plugging $W_{i,t}$ in equation (2) by (3) and solving for $y_{i,t}$ leads to equation (1). Therefore, the regression (1) can be regarded as reduced-form equations for $y_{i,t}$ from a system of structural equations (2) and (3). As such, coefficients β_1 and β_2 in regression (1) can be interpreted as the overall effects of X_i and $Z_{i,t}$.

3.2. Data on Independent Variables

Motivated by existing literature on COVID-19 and economic intuitions, we consider six categories of factors in X_i:

1. Demographic conditions (total population, ratio of population 65 years and above, and population density);
2. Geographic conditions (average temperature and rainfall in March);
3. Economic conditions (GDP per capita and income Gini coefficient);
4. Global interdependency (international visitors and international trade);
5. Healthcare conditions (health expenditure as a share of GDP, number of hospital beds per 1,000 people and SARS outbreak dummy);
6. Public governance (government expenditure as a share of GDP and government effectiveness index constructed by the World Bank).

All these variables are fixed and taking values before 2020. In other words, they are exogenous to the outbreak of COVID-19 in our regression analyses. The data appendix provides detailed definitions and data sources of these variables. Table 2 reports their summary statistics.

<Table 2 here>

Besides X_i, we also include two other explanatory variables in $Z_{i,t}$ as additional controls. The first one is the number of cumulative infections in the rest of the world. This is to control both the potential externality from other countries and the prevailing trend in the course of a global pandemic. The second is the test ratio for COVID-19, defined as the number of people tested for COVID-19 per million people. Including the test ratio into the regressions is one way to mitigate the underreporting concerns.

We consider the test ratio as an equilibrium quantity for testing demand and testing supply in a country. The demand for testing depends on both the severity of COVID-19 and the testing criteria in a country. The supply for testing is mainly determined by the capacity and the willingness to test, which largely depends on its predetermined healthcare conditions and public governance. Therefore, conditional on the healthcare conditions and public governance, if two countries have the same severity of COVID-19, the country with a lower test ratio is more likely to have underreported infection cases due to a stricter testing criterion.

3.3. Main Findings

Tables 3 and 4 report the regression results for equation (1). The dependent variables are cumulative infections and deaths per million people in natural logarithm, respectively. Columns (1) are the benchmark results with full sample. Additional results by addressing data underreporting issues are presented in columns (2) to (4) and discussed in Section 3.5. A series of robustness checks are presented in Tables 5 and 6 and discussed in Section 3.6. Moreover, to allow for time-varying β_1 and β_2, we also run regressions using weekly subsamples in Section 3.4, and plot the coefficient estimates by week in Figures 5 and 6. Across all these regressions, an R^2 around 0.7 to 0.8 suggests that our explanatory variables have a good prediction power for the observed infections and deaths across the world.

<Table 3 and 4 here>

These empirical exercises aim to identify the risk and protective factors for infections and deaths. Potential data underreporting could be a serious concern for interpreting meaningful empirical results. However, the cross-country variations in the reported infections and deaths and explanatory variables are so immense that it is still possible for us to uncover some most significant and robust patterns as our main empirical findings.

First, across the large set of our empirical exercises, we find that *GDP per capita*, *population density* and *Gini coefficient* are the three most important risk factors, and *government effectiveness*, *temperature*, and *hospital beds* are the three most important protective factors, for both infections and deaths.

Figures 3 and 4 visualize our main findings by sorting the risk factors on the right and the protective factors on the left for infections and deaths respectively. The corresponding magnitudes measure the percentage change in infections and deaths per million people due to one standard deviation increase in each of these factors, based on their estimated coefficients in columns (1) of Tables 3 and 4, together with the summary statistics in Table 2.

<Figure 3 and 4 here>

We start our discussion with the effect of GDP per capita on infection. The coefficient 1.044, interpreted as the elasticity of infections with respect to GDP per capita, implies that a country with a 100% higher GDP per capita may expect 104.4% more reported cumulative infections per million people, all else being equal. A unit elasticity of GDP per capita on infection rate is very close to similar studies using cross-country data, such as Goldberg and Reed (2020). The importance of average income may explain a striking fact that among the top 10 countries with the highest infections per million people listed in Table 1, four of them ranked the top 10 countries in terms of GDP per capita in 2018 according to the World Bank.

This somewhat unpleasant finding is consistent with Adda's (2016) findings on incidence of several viral diseases in France over a quarter of a century. It can also be rationalized by common economic sense. As higher GDP per capita implies more market production, consumption and more social activities and interaction among people, leading to more infections. Thus, this finding may indicate that economic activity is a fundamental mechanism for the spread of the epidemic. Reducing GDP per capita is of course undesirable. In contrast, what our cross-country evidence suggests here is the importance of the restrictions imposed on mobility and human-to-human interactions, as highlighted in some researches based on more detailed country-specific evidences, such as Gatto et al. (2020).

Population density is the second most important contributing factor of infections, suggesting that a country with a dense population is more vulnerable to the spread of COVID-19. The elasticity of 0.240 implies that all else being equal, a country with a one standard deviation higher population density than the sample average, expects 84.8% more reported infections per million people. Combining the big impacts of both GDP per capita and population density on reported infections, it is logical to expect large infection numbers in many megacities in developed economies, such as New York City, London, and Milan. It is also not surprising to see serious infections in Singapore,[7] a city-state with one of the highest GDP per capita and the highest population density in the world.

Income inequality measured by *Gini coefficient* is the third most important factor that induces more reported infections. The coefficient 0.048 suggests that on average, a country with a higher Gini coefficient than the cross-country average by one standard deviation could witness 39.1% more cumulative infections per million people. While identifying the exact mechanisms on why inequality could spread COVID-19 is beyond the scope of this paper, our cross-country findings echo the statement of Ahmed et al. (2020) that pandemics rarely affect all people in a uniform way.

Among the three most important protective factors, government effectiveness and hospital beds are of our key interest, as they have directly applicable policy implications. As expected, the government effectiveness contains the pandemic. However, its protective effect is surprisingly remarkable. The coefficient -0.825 suggests that an increase in government effectiveness index by one standard deviation from the sample average, a value close to Italy's, to the value of South Korea, would reduce unit infections by 72.6%, *ceteris paribus*. This corroborates the findings in Lee et al. (2020) that swift and decisive measures taken by government are prominent in containing COVID-19 in the context of South Korea.

[7] Among the total infections of 56,216 as of 21 August 2020, around 95% are workers living in dormitories, who are almost isolated from local communities under current management system.

Another important protective factor comes from the number of hospital beds, a key measure of medical infrastructure. Its coefficient -0.252 suggests that a country with 2.60 hospital beds per 1000 people more than the sample average of 3.33, that is, an increase by one standard deviation, would reduce unit infections by 19.7%, all else being equal. Our finding illustrates that adequate medical infrastructure can effectively reduce the spread of infectious diseases. This is consistent with the findings by Okoi and Bwana (2020) on the importance of access to health services in addressing the COVID-19 outbreak in Sub-Saharan Africa.

As the third robust protective factor, temperature also has a big negative impact on the COVID-19 infections, indicating that a higher temperature is not conducive to the survival and spread of the viruses. The coefficient of -0.047 infers that countries with 11.01 degrees Celsius higher from the sample average (14.78 degrees Celsius) expect 51.7% lower unit infections. This evidence may suggest why countries from Africa and South East Asia, are on average hit relatively less severely by the pandemic. The blessing effect of high temperature is consistent with many epidemic-related researches, such as Bannister-Tyrrell et al. (2020).

Comparison between Figure 3 and Figure 4 also reveals a few interesting findings. First, despite of a slightly smaller magnitude, *GDP per capita*, *population density* and *Gini coefficient* are also the three most important risk factors for death. Second, the magnitudes of the three common protective factors are even more pronounced on deaths than on infections. In particular, the coefficients of *hospital beds* and *temperature* in column (1) of Table 4, -0.732 and -0.069, are 2.9 and 1.5 times of their corresponding coefficients for infections reported in column (1) of Table 3. Thus, increasing one standard deviation from their sample averages results in a reduction of deaths by 57.2% and 76.0%, respectively. This suggests that people in a country in a warmer region with more prepared hospital beds, and a more effective government, face a much lower risk of death due to COVID-19. Third, besides these common factors, *SARS outbreak* is another important risk factor for infection; and proportion of elderly is another important risk factor for death.

SARS outbreak, as a dummy being one if a country reported probable cases of SARS in 2003, is shown to have a big protective effect on infection. All else being equal, countries with SARS imprint see a lower cumulative infection by 40.8%. Several possible mechanisms have been examined in the literature. Countries that had experienced SARS in 2003 are more cautious about COVID-19 and could have taken anti-epidemic measures more timely and more strictly, a mechanism emphasized in Ru et al. (2020). Wan et al. (2020) find that Hong Kong's experiences during the SARS outbreak in 2003 also makes its civil society more prepared in containing COVID-19. Similarly, Angeli and Montefusco (2020) believe it is easier for people in countries that experienced SARS to adapt to measures such as social distancing and facemask.

The proportion of *population aged 65 and above*, has a coefficient of 0.009 in Column (1) of Table 4. This suggests that age is an important risk factor of death: a country with 18% elderly population, which is one standard deviation higher than the world average of 11.2%, will expect to have 6.03% more deaths than the world average, *ceteris paribus*. The importance of age gradient in risk of death echoes many findings from medical literature, for example Verity et al. (2020). On the other hand, the evidence that the elderly are more vulnerable to COVID-19 could deter them from social interaction, and thus leads to a negative association between proportion of elderly population and infection rate, as indicated in column (1) of Table 3.

Besides these predetermined country characteristics, two control variables – the number of cumulative infections in the rest of the world and the test ratio, are also found to have significant positive correlation with cumulative infections and deaths. This outcome can be considered as a pass of model appropriateness check. Consistent with our expectation, a strong positive correlation between the infections in a country and the infections in the rest of the world highlights the nature of a global pandemic. The infection in the rest of the world could aggravate the infection and death in a single country, which in turn exacerbates the infection and death in other countries. In addition, a strong positive correlation between the infection in a country and its test ratio is also well expected: countries with more infection and death demand more testing; while a higher test ratio reduces the extent of underreporting which contributes to the reported infection and death ratio.

3.4. Results using weekly subsamples

To allow for the possibility of time-varying coefficients, we run regression (1) using weekly subsamples. To visualize our findings, we plot the estimates together with their 95% confidence intervals by week in Figure 5 for infections, and in Figure 6 for deaths. As there could be many random factors in the first week of an epidemic and there are too few observations in the later weeks, only results from week 2 to week 20 are presented.

<Figure 5 and 6 here>

Consistent with Tables 3 and 4, same set of risk and protective factors are also identified in Figures 5 and 6, using weekly subsamples. More interestingly, a salient pattern is that the magnitude of some risk factors and protective factors do change over time, suggesting the importance of different factors along the course of the pandemic.

In line with our common sense, except the epicenter, for the rest of the world, the initial infections are imported from overseas at the beginning of the pandemic. Therefore, global interdependency, measured by either international trade or international visitors, is a prominent risk factor in early weeks, a finding consistent with Zimmermann et al. (2020). As expected, its importance generally declines after governments take border controls or closure. On the contrary, whether a country has had a SARS outbreak is a prominent protective factor in early weeks. However, when the pandemic evolves, after 6 to 8 weeks according to our regressions, domestic and contemporaneous factors become more important. For example, the magnitudes of GDP per capita, population density, Gini coefficient, government effectiveness, temperature, and hospital beds on deaths are generally increasing over the weeks of our sample.

3.5 Addressing Underreporting

There have been many media reports, based on anecdotes and some anatomies, on how individual countries may have omitted or concealed infection and death cases. The academia has tried to infer the magnitude of underreporting under various assumptions and with the auxiliary of some additional information, such as Bommer and Vollmer (2020), Hortaçsu et al. (2020), Li et al. (2020), and Stock et al. (2020). However, most of these researches focus on individual countries. The estimated magnitude also varies vastly across different researches. To address the underreporting issue in a cross-country setup, we first show evidences from our empirical analyses that are consistent with the presence of underreporting. This motivates us to adjust our dependent variables in a systematic way to address underreporting. We then examine whether our main findings are robust to such adjustment.

In columns (1) of Tables 3 and 4, we have reported the full sample for infection and death regressions. Interestingly, health expenditure and government expenditure are significantly positive for both infections and deaths, which seems to be counterintuitive. However, if we focus on the subsample of countries with top 25% COVID-19 virus test ratios reported in columns (2), government expenditure has a significant negative impact on deaths, while no longer induces infections. Similarly, health expenditure significantly reduces infections and the positive impact on deaths becomes smaller as well. These patterns seem to be consistent with our conjecture that the confirmed infection and death data are subject to underreporting.[8]

Motivated by these empirical findings, we adjust the infection data by the country-specific universal health coverage (UHC) index and the voice and accountability (VA) index. The UHC index, provided by the World Bank, measures coverage index for essential health services that people have access to without financial hardship, including services of reproductive, maternal,

[8] Countries with higher health expenditures or government expenditure, on the one hand, may have a better medical system or public sector, which will contribute to reducing the infection and death. On the other hand, these countries could be more confident to roll back COVID-19, resulting in less underreporting and more confirmed cases. Thus, the regression coefficients are the joint outcome of these two opposing forces. All else being equal, countries with a higher test ratio on average are less likely to underreport and are more likely to deliver reliable results. This explains why healthcare expenditure and government expenditure have different or opposite effects in the full sample and in the sub-sample.

newborn and child health, infectious diseases, and non-communicable diseases. UHC is presented on a scale of 0 to 100, and a higher index suggests stronger medical capability and easier access to health services. The VA index is provided by the Worldwide Governance Indicators. It reflects the degree of freedom of people in a country, including participation in selecting their government, freedom of expression, freedom of association, and free media. We normalize the VA index from the original -2.5 to 2.5 into a scale of 0 to 100, too, where a higher index implies a louder voice of people and more transparent information.

Presumably, the magnitude of underreporting in a country is largely determined by its testing regimes and reporting guidelines, which should be inversely related to UHC and VA.[9] Thus we modify our dependent variables by multiplying the number of infection or death with the square root of (100 – UHC) or (100 – VA) in two separate robustness checks, reported in columns (3) and (4) in Tables 3 and 4. Under this adjustment, for a country with the lowest UHC or VA, we assume its actual infections and deaths are nine times larger than the reported numbers, still a conservative scale among the recent researches. For the rest countries, the magnitude of underreporting decreases with UHC and VA in a declining fashion. Thus, we assume that unless a country has the full score in UHC and VA, there is always some underreporting. As we obtain in Tables 3 and 4, no matter whether the adjustment index is UHC or VA, the results in columns (3) and (4) are very similar to those in columns (1) of Tables 3 and 4. This implies that our main findings are robust to underreporting, at least to the type of adjustment we have applied.

3.6 Robustness Checks

We conduct a set of robustness checks and present the results in Tables 5 and 6 for infections and deaths, respectively. First, we include month dummies in columns (1). It turns out that the results are consistent with the benchmark findings in Tables 3 and 4. Moreover, the coefficients of the dummies generally increase over time, which motivates our second robustness check. In columns (2) and (3), we divide the full sample into two subsamples, January to April and May to August. As shown, most of the risk factors in column (3) have significantly larger coefficients than those of column (2), again suggesting the massive transmission of virus at a later stage. Next, we randomly choose one week, that is the 11th week after first reported case to examine whether our results are driven by a long time-series of data. As indicated in columns (4) the most important risk and protective factors remain valid even within a much shorter sample period, indicating that our findings mainly come from cross-country variations in predetermined characteristics.

<Table 5 and 6 here>

[9] By analyzing all available data on international COVID-19 cases from 20 January until 18 February, Lau et al. (2020) find those countries with lower Healthcare Access and Quality (HAQ)-index either may underreport COVID-19 cases or are unable to detect them adequately. The HAQ and UHC index are highly correlated with a coefficient of 0.86. We obtain very similar results for columns (3), if we adjust the infection and death data with HAQ.

The next set of robustness checks investigate whether our results are sensitive to the sample of countries included. In columns (5) of Tables 5 and 6, we exclude countries with population sizes less than two million. In columns (6), we exclude countries with population density above 1,000 people per square kilometer. The results are generally similar compared to those of columns (1) in Tables 3 and 4. This suggests that our findings are not driven by including either too small countries or too crowded countries. An additional robustness check is to exclude China, the initial epicenter of the COVID-19. As the mechanism of infection and death could be different in the epicenter and in the rest of the world, it is important to know whether our findings are robust by excluding China from the sample. Columns (7) show that excluding the initial epicenter from our sample has little impact on our main findings.

Another robustness check is on the definition of $Days_{i,t}$. For some countries, such as the US, there has been a long-time gap between the first imported case and the subsequent large-scale outbreak. Thus instead of days since the first infection, we define $Days_{i,t}$ as the days since the first 50 infections to check whether this has any effect on our findings. We report the results in column (8) of Table 5. The importance of SARS outbreak declines while the effects of hospital beds and government effectiveness are even more pronounced. Both of these changes are consistent with our expectation, and echo the time-varying patterns of parameters highlighted in Figure 5.

Finally, we also experiment with an alternative measure for the death rate. In our main results, the death rate is defined as the number of deaths per million people. An alternative definition is the CFR, which represents the proportion of deaths among all the infected individuals. Presumably, the data on CFR is more likely subject to measurement error problem, as it depends on two variables: the denominator – infection and the numerator – death. The reporting guidelines for infection, and for death, could vary substantially across countries or even over time within a country. Thus, we only restrict our analyses to those countries with the highest 25% test ratios. The results are reported in column (8) of Table 6. Similar to other columns of Table 4, population density and proportion of the elderly are most important risk factors, while hospital beds and government effectiveness remain to be the most important protective factors. What is more interesting is that the magnitudes of all these factors are even larger for CFR than for the number of deaths per million people. Particularly, the magnitude of population 65+ has increased nearly 18 times from 0.009 in the benchmark to 0.161. This suggests that conditional being infected, age is the most prominent risk factor for death.

4. A Global Ranking

In Section 3, risk factors and protective factors have been identified to explain the huge cross-country variations observed in cumulative infections and deaths, even after being normalized by population size. By controlling for these predetermined factors, this section provides a refined global ranking on cost efficiency of infections and deaths. The rankings and efficiency scores can be regarded as an indirect and holistic inference on how effective the pandemic public policies have been on restraining infection and reducing death relative to other countries.

The ranking methodology is based on the stochastic frontier analysis literature. The idea is to treat regression equation (1) as cost functions in light of medical costs (or value of a statistical life) associated with COVID-19 infections (or deaths). For the convenience of presentation, consider the error term from equation (1) for now. A one-sided inefficiency term $u_i > 0$ is assumed in the error term so that,

(4) $$\varepsilon_{i,t} = u_i + v_{i,t},$$

where zero-mean $v_{i,t}$ is considered as a measurement error. It is reasonable to assume that the inefficiency term u_i is constant over time during a short time period. A larger value of u_i implies higher costs associated with infections or deaths and the corresponding country i is less cost efficient.

Kumbhakar et al. (2015) summarize several approaches to estimate cost efficiency in stochastic frontier models with cross-sectional data and panel data, including maximum likelihood estimation, corrected ordinary least squares (COLS) and panel data methods. To be in line with coefficient estimation results in Section 3, COLS is adopted here. Denote e_{it} the pooled OLS residual obtained from equation (2): $e_{i,t} = y_{i,t} - \hat{y}_{i,t}$. Since $e_{i,t}$ is a consistent estimator of $\varepsilon_{i,t}$ in (4), a COLS estimator of cost efficiency can be defined as $\exp(min_j e_{j,t} - e_{i,t})$ for country i on day t. However, its accuracy could be contaminated by the presence of the zero-mean random shock $v_{i,t}$ in the error term $\varepsilon_{i,t}$. To smooth out $v_{i,t}$, time-average of $e_{i,t}$, or $\bar{e}_i = \frac{1}{T}\sum_{t=1}^{T} e_{i,t}$, is used as an estimator of inefficiency u_i over a time period. A country with a smaller value of $\bar{e}_i$ tends to have a higher efficiency ranking. Intuitively, its actual infections (or deaths) are smaller relative to its model predictions. Thus, one COLS cost efficiency estimate can be defined as $E_i = \exp(min_j \bar{e}_j - \bar{e}_i) > 0$. E_i decreases with $\bar{e}_i$ and achieves the maximum value of 1 for a country with the minimal value of $\bar{e}_i$, which lies on the efficiency frontier.

A more convenient cost efficiency score is defined as

(5) $$CE_i = [\frac{max_j \bar{e}_j - \bar{e}_i}{2(max_j \bar{e}_j - min_j \bar{e}_j)} + 0.5] \times 100.$$

In the same spirit as the two-side technical efficiency measure proposed by Feng and Horrace (2012), CE_i has the advantage of having a same scale across the sample, so that efficiency differences among different countries are comparable and the efficiency scores are cardinal. Since the three efficiency estimators $-\bar{e}_i$, E_i and CE_i must deliver the same ranking, here we focus on CE_i for convenience. Using CE_i, the most (cost) efficient country achieves a score of 100 and the least one scores 50.

We rank all 100 countries in our sample by using their corresponding 14-day averaged residuals $\bar{e}_i$ obtained from regression (1) in respective pandemic weeks. The full list of ranking is available on our webpage. We will constantly update and extend the list with the progression of the pandemic. Here we use Figure 7 and Figure 8 to present the infection and death rankings of 10 selected countries. Once again, as the rankings are in terms of cost efficiency, countries with a smaller number of ranking are more effective in constraining the pandemic.

For infection, to rule out the big randomness in the early days of infection, we use the $\bar{e}_i$ from column (8) of Table 5, that is after the first 50 confirmed infection cases for our ranking exercises. In this way, we are comparing China on 4 January with Italy on 23 February, the US on 24 February and the UK on 3 March, and onwards. As we observe from Figure 7, during the first 3 to 4 weeks after the first 50 confirmed infection cases, the US performed the best in terms of infection among the 99 countries. In comparison, China's ranking is at the very bottom because the spread of virus in China was drastically fast during its initial stage. Thanks to the prompt responses, massive resource mobilization and strict containment policies, its ranking improves steadily over time. By early August, China achieves the 8th spot out of 89 countries, indicating that the COVID-19 has been effectively contained. In contrast, the ranking for the US has been declining quickly since week 7 to 8, consistent with the massive outbreak in the US starting at the end of March. Nevertheless, at the end of our sample period, despite the US has the world's highest number of infections, its efficiency ranking is 56th out of 89. This suggests the importance of controlling for the risk factors and protective factors for a fair global ranking. Overall, Japan has a steady and high efficiency ranking over the whole sample period. South Korea, New Zealand and Italy improve their rankings over time, while countries such as Brazil and Spain perform persistently below the average.

<Figure 7 and 8 here>

For death, except China, Iran and Philippines, the rest of countries in the sample with death cases either have their first death case in March and April or at least three weeks after their first confirmed infection case. Thus we use the $\bar{e}_i$ from column (1) of Table 4, that is since first confirmed death case as a common starting point for our ranking exercises. Similar to Figure 7, Figure 8 shows that Brazil, Spain and UK have been performing persistently poorly, while New Zealand, South Korea and Japan, are among the most efficient group, only next to those countries without reported deaths.

Interestingly, Singapore's ranking in terms of death is constantly high, which is vastly different from its infection ranking in Figure 7. In other words, despite its high cumulative infections due to the massive dormitory transmission among migrant foreign workers, the number of its cumulative deaths is one of the lowest in the world. This is consistent with its advanced health infrastructure and well-known government effectiveness, two most important protective factors for death highlighted by our empirical exercises.

5. Conclusion

So, what does cross-country data tell us about COVID-19? First, the substantial variation in the cross-country infections and deaths is indeed associated with many contributing factors. Our empirical exercises suggest that countries with a higher population density, more senior citizens, lower temperatures, a higher average income, more income inequality, and more connectedness with rest of the world, are predicted to be more vulnerable to the global pandemic. Although most of these factors are either impossible or undesirable to change, there are certainly other factors that countries could improve, for example, the healthcare infrastructure, and in particular, the effectiveness of a government.

Second, the cross-country regression analyses allow us to identify groups of countries that are exceptionally better or worse than predicted in a systematic way. As our ranking exercises can be regarded an indirect and holistic inference on the pandemic policy efficiency, it could help policymakers to think why one country might be doing better than another, and what they can learn from that. For example, Edwards (2020) claims that the relative success of New Zealand in managing the virus could provide an opportunity for countries in the Pacific region to explore the pathway of recovery from COVID-19. We also find the importance of some risk and protective factors does change over time. This could be useful to policy makers in those countries hit by the pandemic later than other countries to make good use of the protective factors and to best prevent or respond to risk factors.

Last but not least, this paper is one of the very early attempts that aim to understand the COVID-19 pandemic from a social-economic perspective. Our results are subject to two important limitations. One is the underreporting concerns, and another is the evolving situation of the pandemic itself. As more reliable data become available and the pandemic unfolds, we will keep updating our analyses and rankings. After all, until COVID-19 is completely over it will not be possible to know for sure which countries have dealt with the virus better than others. That is when we can really learn the lessons for next time, as some countries have learned from the SARS outbreak for COVID-19.

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Figure 1-8

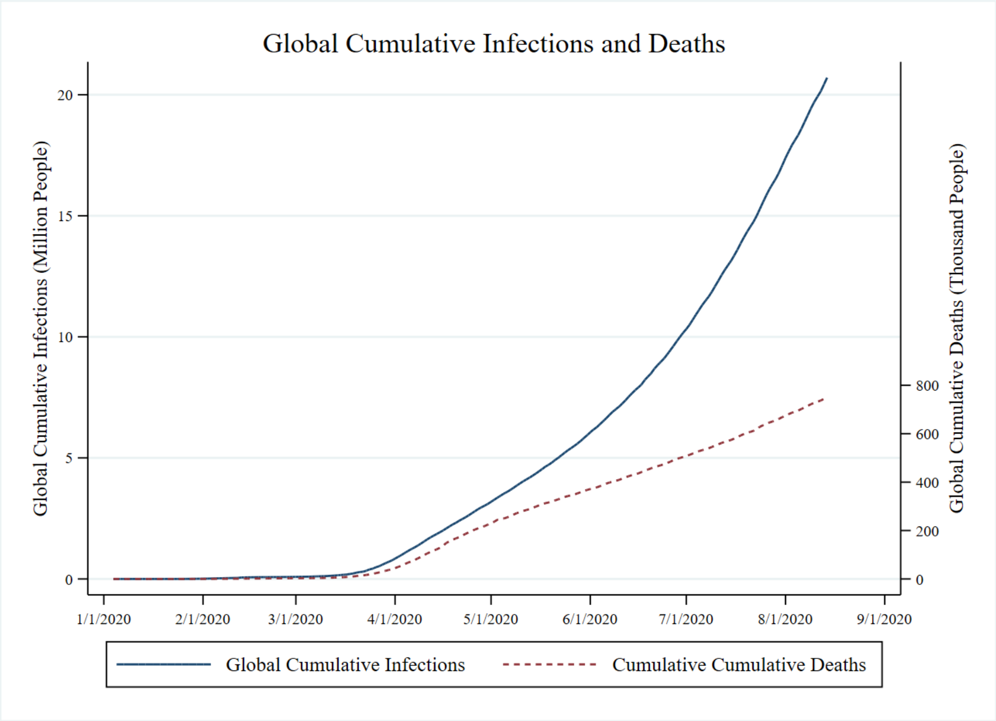

Figure 1a: Global Cumulative Infections and Deaths

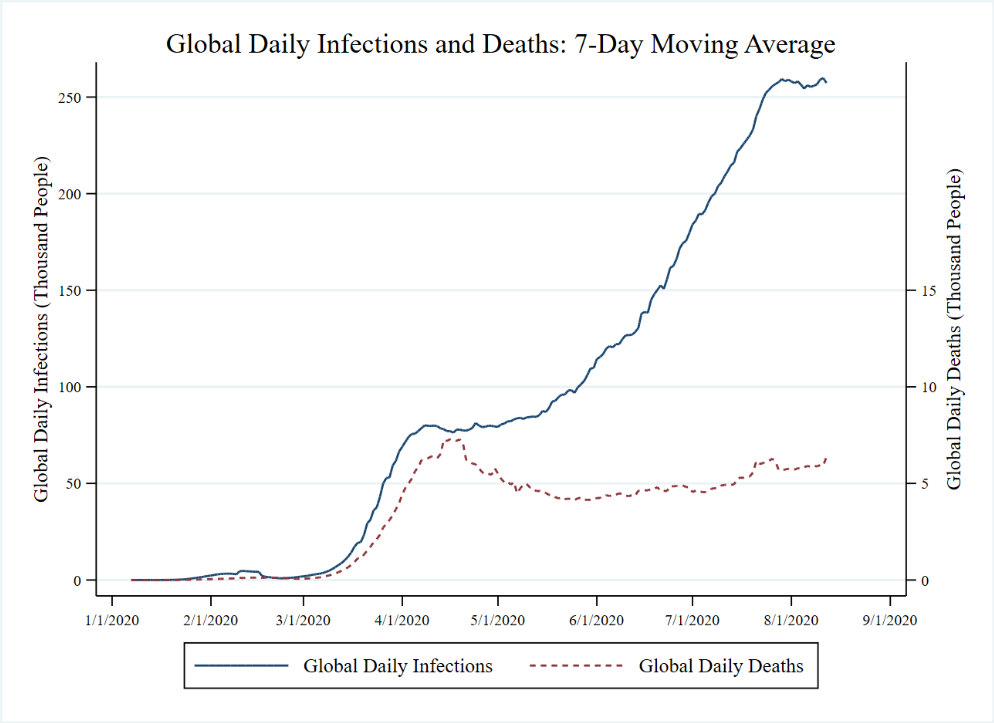

Figure 1b: Global Daily Infections and Deaths

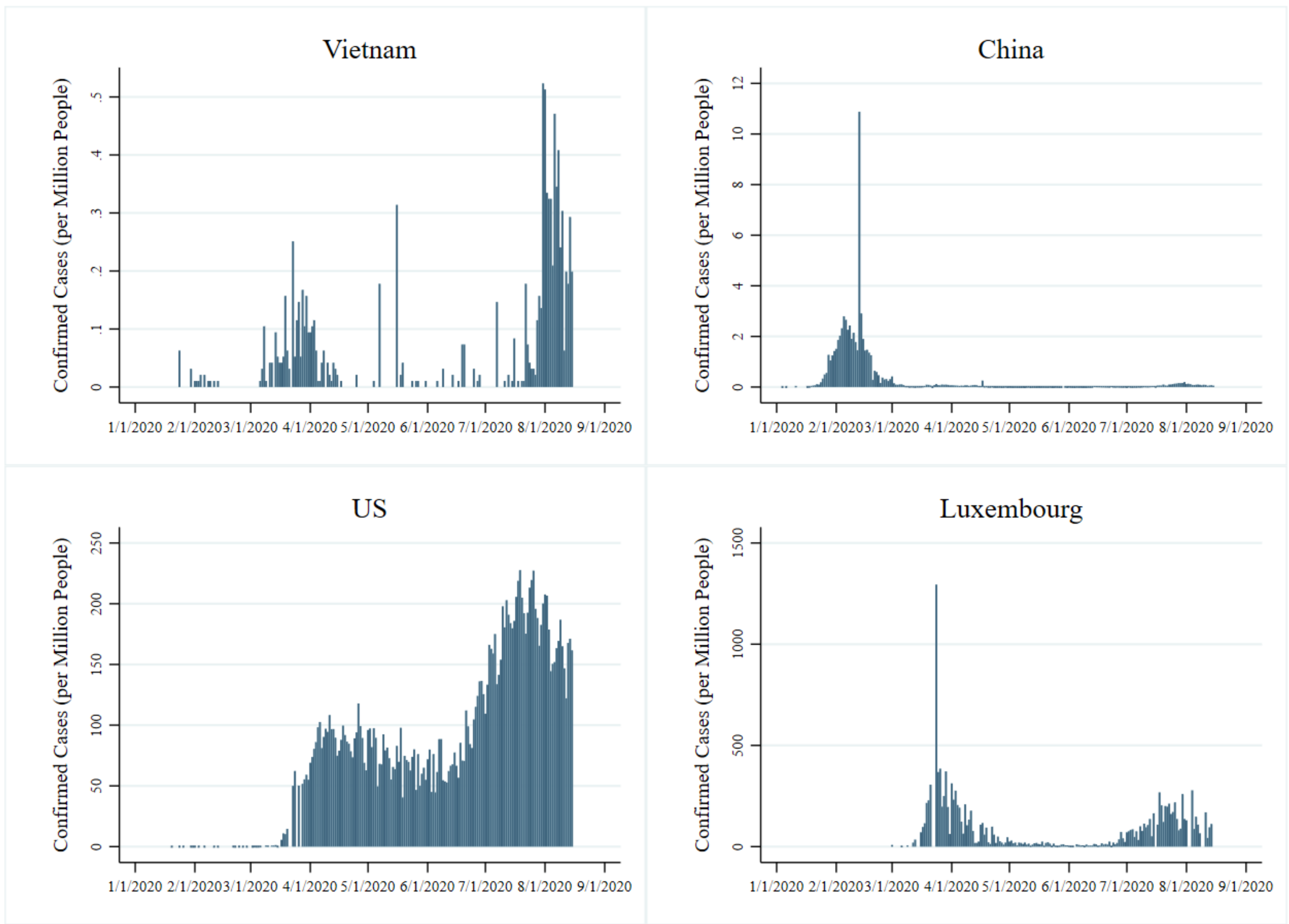

Figure 2: Daily Infections of Four Representative Countries

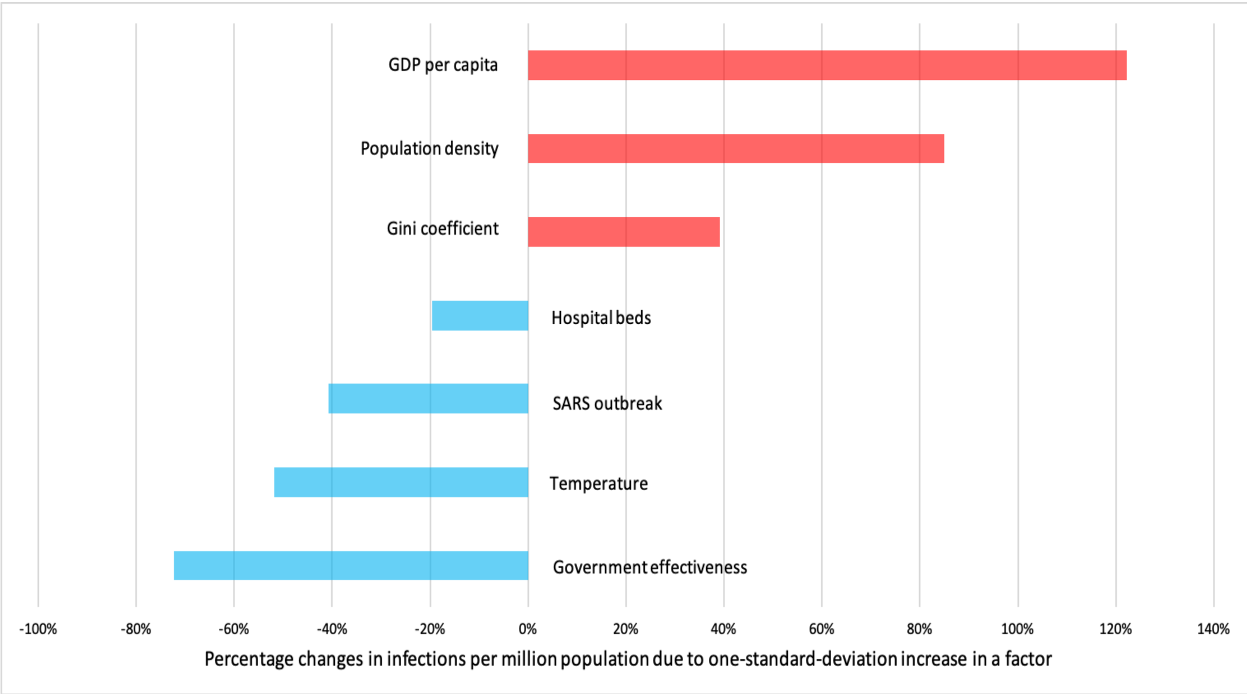

Figure 3: Magnitude of Risk and Protective Factors on Infections Per Million People

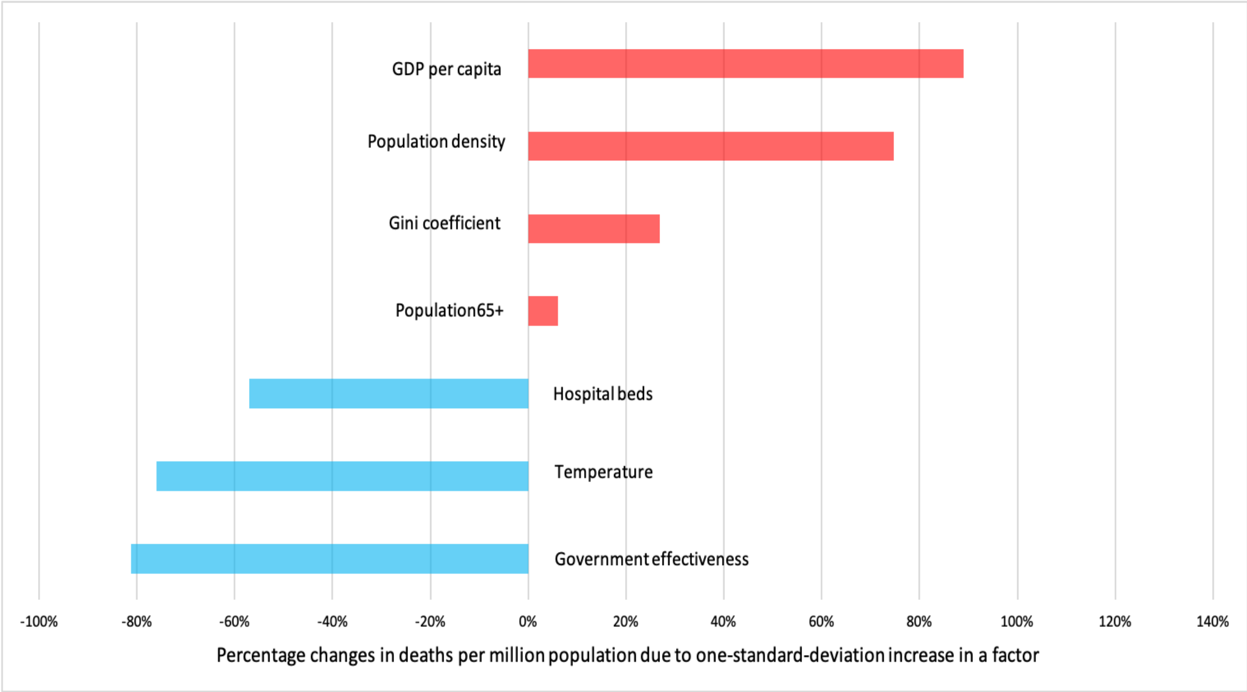

Figure 4: Magnitude of Risk and Protective Factors on Deaths Per Million People

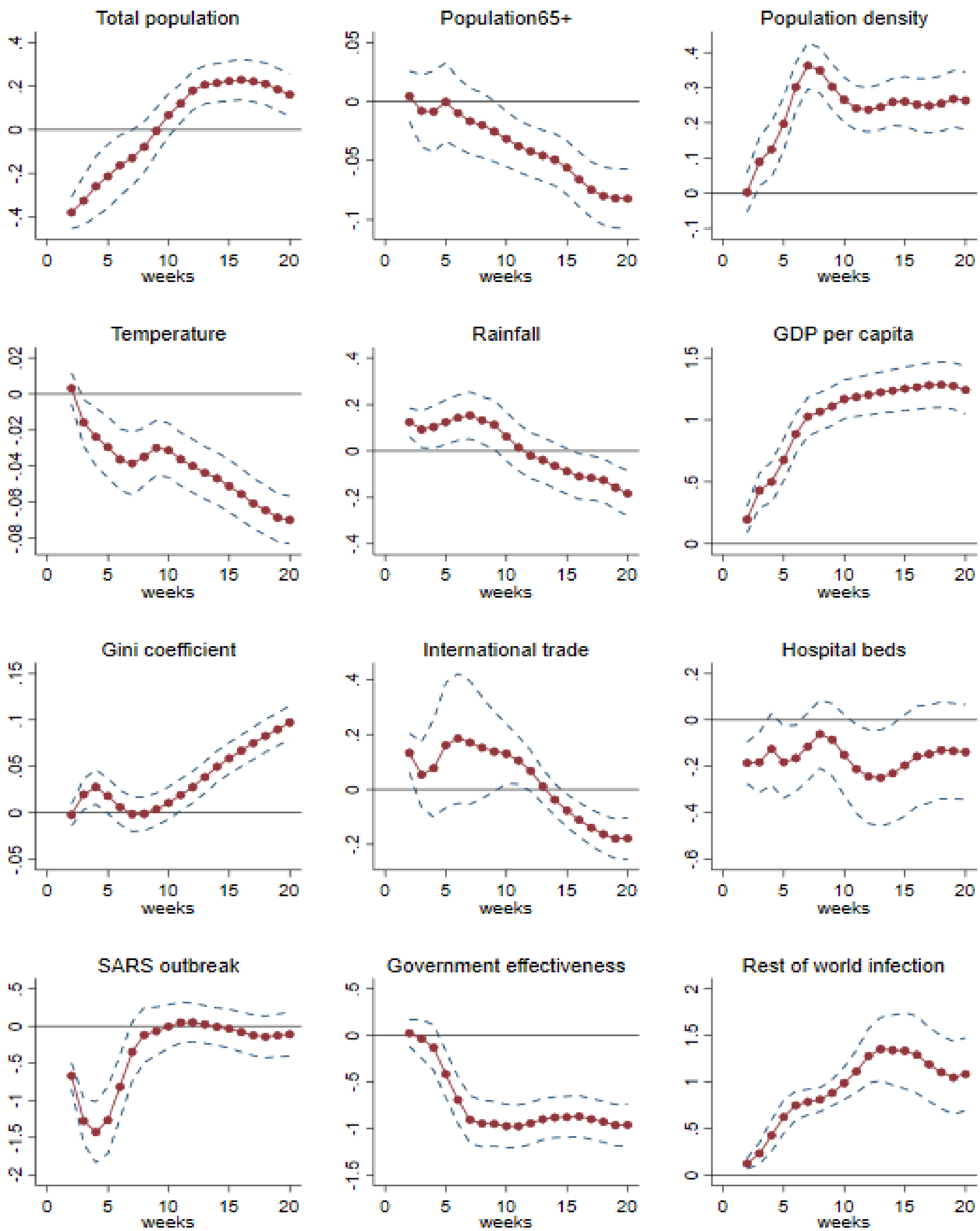

Figure 5: Estimates of Infection Regression over Time

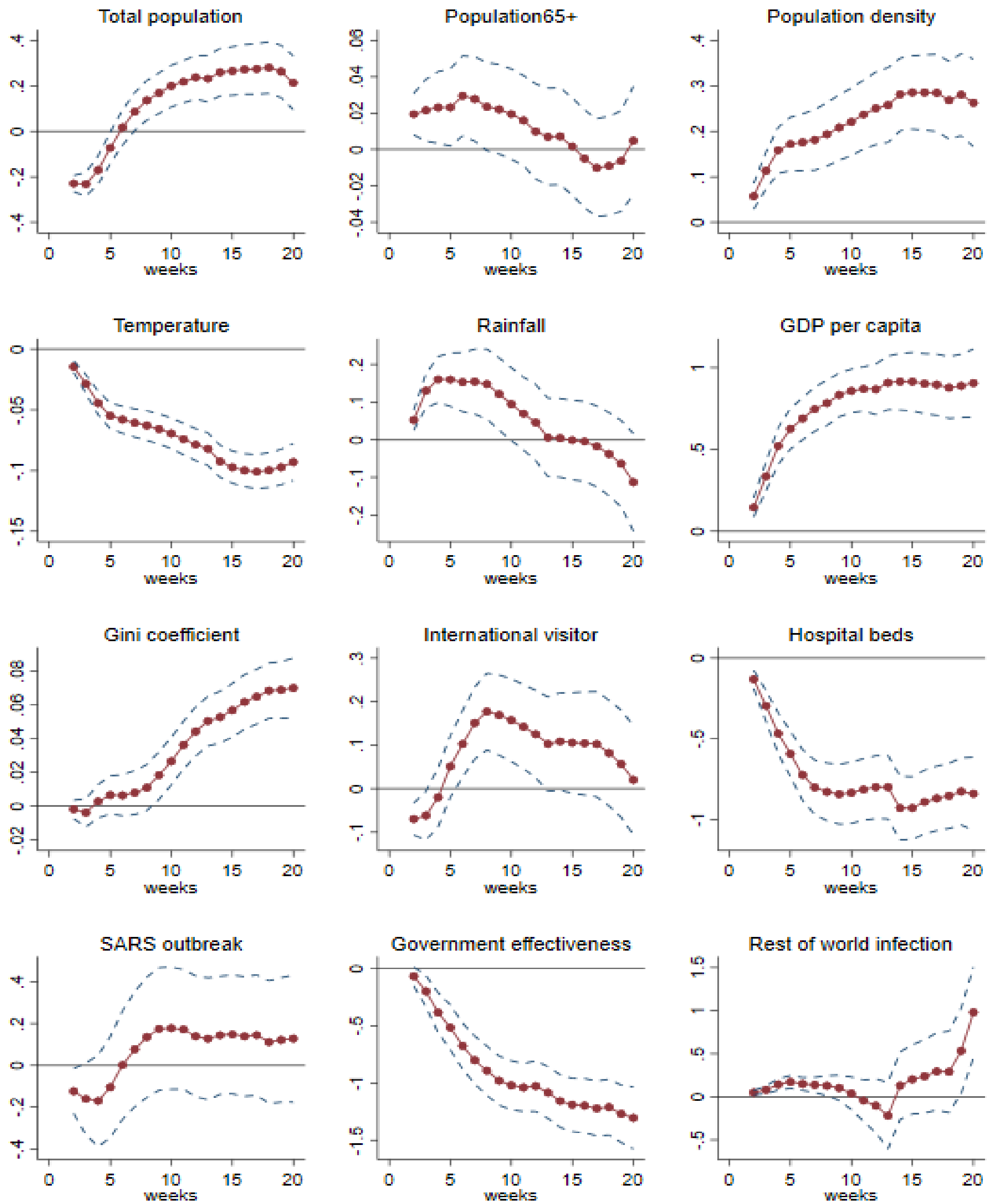

Figure 6: Estimates of Death Regression over Time

Figure 7: Ranking for Infection Cost Efficiency for 10 Representative Countries

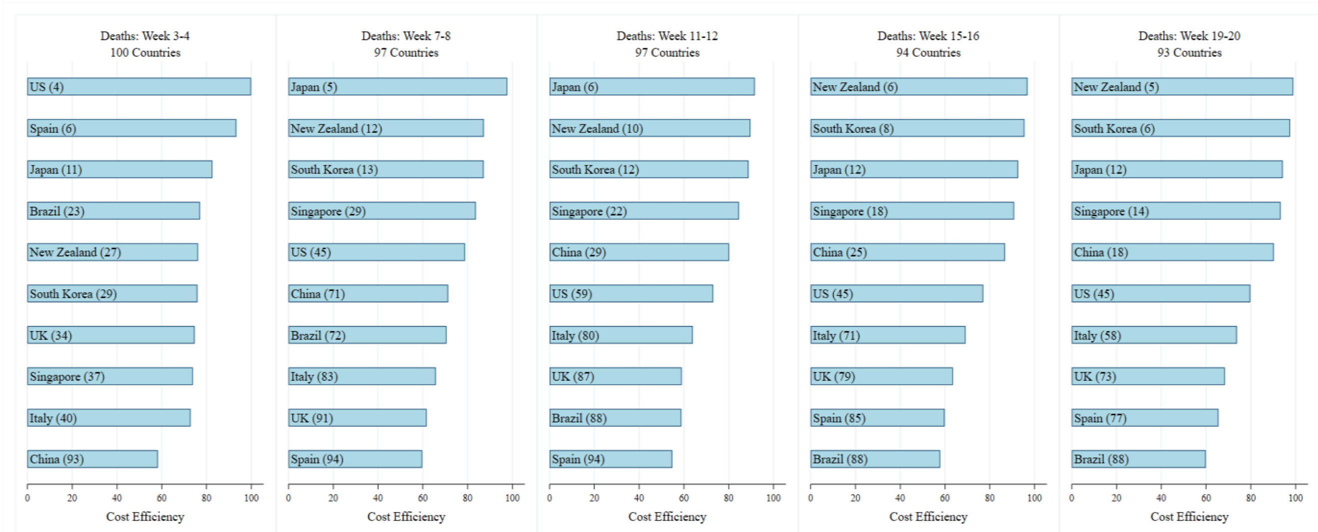

Figure 8: Ranking for Death Cost Efficiency for 10 Representative Countries

Table 1 Cumulative Infections and Deaths: Summary Statistics and Worst and Best 10 Countries

Variables	Unit	Mean	Median	Std. D	Min	Max	Worst 10	Value	Best 10	Value	Form in regression
Cumulative infections	per million people	3,998	1,833	5,788	3	41,174	Qatar	41,174	Laos	3	log
							Chile	20,402	Myanmar	7	
							Panama	18,781	Vietnam	10	
							US	15,927	Cambodia	17	
							Peru	15,880	Uganda	32	
							Brazil	15,395	Thailand	49	
							Armenia	13,991	Angola	60	
							Luxembourg	12,119	Burkina Faso	63	
							South Africa	10,023	China	64	
							Israel	9,962	Mozambique	92	
Cumulative deaths	per million people	131	46	195	0	867	Belgium	867	Laos	0	log
							Peru	802	Bhutan	0	
							UK	703	Cambodia	0	
							Spain	611	Myanmar	0	
							Italy	583	Vietnam	0	
							Sweden	568	Uganda	0	
							Chile	552	Sri Lanka	1	
							US	508	Mozambique	1	
							Brazil	503	Rwanda	1	
							France	452	Thailand	1	
Case fatality rate (CFR)	ratio	3.3%	2.3%	3.2%	0.0%	15.4%	France	15.4%	Laos	0.0%	ratio
							UK	14.9%	Bhutan	0.0%	
							Italy	14.0%	Cambodia	0.0%	
							Belgium	13.0%	Singapore	0.0%	
							Hungary	12.6%	Qatar	0.2%	
							Mexico	10.9%	Botswana	0.2%	
							Netherlands	10.1%	Rwanda	0.4%	
							Spain	8.5%	Sri Lanka	0.4%	
							Canada	7.4%	Nepal	0.4%	
							Sweden	6.9%	Iceland	0.5%	

Data source: World Health Organization (as of 15 August 2020)

Statistics are computed from 100 countries.

Table 2 Summary Statistics for Independent Variables

	Variables	Unit	Mean	Std. D	Min	Max	Form in regression	Source
1	total population	million	66.90	196.56	0.35	1392.73	log	World bank
2	population 65+	%	11.2	6.7	1.1	27.6	%	World bank
3	population density	per square kilometer	229	809	3	7,953	log	World bank
4	temperature	℃	14.78	11.01	-15.17	31.91		CCKP
5	rainfall	millimeter	63.65	56.66	0.00	356.37	log	CCKP
6	GDP per capita	dollars	20,436	23,929	499	116,597	log	World bank
7	Gini coefficient		37.44	8.15	24.20	63.00		World bank
8	international visitors	per million people	780,549	1,089,944	4,552	6,644,912	log	World bank
9	international trade		0.88	1.63	0.00	10.85		UN Comtrade
10	health expenditure	%	6.91	2.65	2.27	17.06	%	World bank
11	hospital beds	per thousand people	3.33	2.60	0.30	13.40	log	World bank
12	SARS outbreak		0.26	0.44	0	1	0 or 1	WHO
13	government expenditure	%	16.36	4.98	4.93	30.05	%	World bank
14	government effectiveness		0.38	0.88	-1.07	2.23		WGI
15	rest of world infections		5,064,518	5,924,947	0	20,730,436	log	WHO
16	test ratio	per million people	13,081	45,884	0.644	450,019	log	HDX

For data definitions and sources, see data appendix.

Table 3 Reported Infections: Regression Results

Dependent variable	log of infections per million population			
	(1)	(2)	(3)	(4)
sample	Full	TOP25	UHC adjusted	VA adjusted
Days	0.052***	-0.021***	0.054***	0.056***
	(31.719)	(-6.580)	(30.471)	(31.657)
$Days^2$	-0.000***	-0.000	-0.000***	-0.000***
	(-34.775)	(-0.408)	(-35.387)	(-36.243)
total population	0.014	0.299***	-0.026**	0.019
	(1.225)	(12.766)	(-2.076)	(1.454)
population 65+	-0.045***	-0.002	-0.044***	-0.068***
	(-14.848)	(-0.191)	(-13.975)	(-21.403)
population density	0.240***	0.131***	0.243***	0.257***
	(29.256)	(11.064)	(28.249)	(29.061)
temperature	-0.047***	-0.033***	-0.049***	-0.045***
	(-28.619)	(-15.744)	(-27.017)	(-25.399)
rainfall	0.010	0.253***	-0.003	0.007
	(0.867)	(5.183)	(-0.290)	(0.599)
GDP per capita	1.044***	1.502***	0.982***	1.035***
	(53.256)	(24.700)	(48.145)	(50.438)
Gini coefficient	0.048***	0.059***	0.051***	0.046***
	(24.564)	(14.295)	(24.512)	(22.177)
international visitors	-0.041***	0.554***	-0.053***	0.003
	(-3.030)	(14.619)	(-3.624)	(0.232)
international trade	-0.044***	0.146***	-0.014	-0.002
	(-3.851)	(8.668)	(-1.122)	(-0.184)
health expenditure	0.062***	-0.111***	0.044***	0.043***
	(9.899)	(-8.983)	(6.539)	(6.341)
hospital beds	-0.252***	-0.313***	-0.252***	-0.128***
	(-11.480)	(-5.276)	(-10.683)	(-5.443)
SARS outbreak	-0.408***	-0.205***	-0.473***	-0.444***
	(-11.570)	(-3.366)	(-12.609)	(-12.059)
government expenditure	0.028***	0.013*	0.026***	0.033***
	(9.897)	(1.914)	(8.675)	(10.862)
government effectiveness	-0.825***	-0.798***	-0.795***	-0.954***
	(-30.503)	(-16.802)	(-27.516)	(-33.241)
rest of world infections	0.517***	1.708***	0.651***	0.641***
	(19.745)	(32.534)	(22.829)	(23.009)
test ratio	0.340***		0.334***	0.362***
	(39.058)		(36.423)	(39.593)
Number of observations	17,285	4,494	17,285	17,285
R-squared	0.784	0.859	0.781	0.784

Notes:

1. t-values are reported in parentheses. The stars *, ** and *** indicate the significance at 10%, 5% and 1%.
2. Days stands for the number of days since first infection case.
3. Column (2) reports results of a subsample of 25 countries with the hightest test ratio.
4. Columns (3) and (4) report results of using infections adjusted by UHC and VA indices to address underreporting concern. UHC and VA refer to the universal healthcare and voice and accountablity indices, respectively, constructed by the World Bank.

Table 4 Reported Deaths: Regression Results

Dependent variable	log of deaths per million population			
	(1)	(2)	(3)	(4)
sample	Full	TOP25	UHC adjusted	VA adjusted
Days	0.041***	0.029***	0.053***	0.054***
	(43.521)	(12.258)	(50.674)	(51.408)
$Days^2$	-0.000***	-0.000***	-0.000***	-0.000***
	(-33.376)	(-15.871)	(-41.581)	(-42.964)
total population	0.139***	0.506***	0.120***	0.165***
	(12.961)	(25.945)	(9.968)	(13.695)
population 65+	0.009***	0.105***	0.013***	-0.008**
	(3.325)	(14.626)	(4.205)	(-2.487)
population density	0.211***	0.147***	0.235***	0.249***
	(24.435)	(13.780)	(24.333)	(26.174)
temperature	-0.069***	-0.072***	-0.077***	-0.075***
	(-45.018)	(-41.378)	(-44.486)	(-45.065)
rainfall	0.056***	0.763***	0.031**	0.035***
	(4.991)	(16.407)	(2.487)	(2.832)
GDP per capita	0.760***	1.517***	0.796***	0.866***
	(41.868)	(28.902)	(38.412)	(41.435)
Gini coefficient	0.033***	0.047***	0.041***	0.037***
	(19.440)	(13.984)	(19.820)	(18.219)
international visitors	0.103***	0.174***	0.102***	0.145***
	(8.786)	(4.922)	(7.565)	(10.804)
international trade	-0.085***	0.167***	-0.079***	-0.062***
	(-10.510)	(13.531)	(-8.782)	(-7.096)
health expenditure	0.161***	0.083***	0.159***	0.158***
	(33.425)	(6.787)	(29.372)	(29.408)
hospital beds	-0.732***	-1.215***	-0.794***	-0.684***
	(-34.410)	(-26.070)	(-33.369)	(-28.960)
SARS outbreak	0.103***	-1.742***	0.060*	0.077**
	(3.331)	(-31.377)	(1.774)	(2.345)
government expenditure	0.019***	-0.075***	0.018***	0.025***
	(7.574)	(-13.515)	(6.366)	(8.895)
government effectiveness	-0.926***	-1.483***	-1.056***	-1.227***
	(-36.259)	(-37.398)	(-36.490)	(-43.514)
rest of world infections	0.193***	0.638***	0.263***	0.279***
	(12.214)	(14.165)	(14.910)	(15.882)
test ratio	0.175***		0.210***	0.242***
	(21.977)		(22.854)	(26.416)
Number of observations	14,119	3,793	14,119	14,119
R-squared	0.682	0.771	0.688	0.698

Notes:

1. t-values are reported in parentheses. The stars *, ** and *** indicate the significance at 10%, 5% and 1%.
2. Days stands for the number of days since first death case.
3. Column (2) reports results of a subsample of 25 countries with the hightest test ratio.
4. Columns (3) and (4) report results of using infections adjusted by UHC and VA indices to address underreporting concern. UHC and VA refer to the universal healthcare and voice and accountablity indices, respectively, constructed by the World Bank.

Table 5 Robustness Checks for Infections Regressions

Dependent variable	log of infections per million population							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
sample	Dummy	Jan-April	May-Aug	11th Week	Pop. 2M+	Density 1K-	no China	50 Cases
Days	0.048***	0.079***	0.042***		0.054***	0.052***	0.035***	0.057***
	(32.349)	(27.080)	(18.614)		(33.378)	(31.793)	(23.012)	(48.928)
$Days^2$	-0.000***	-0.000***	-0.000***		-0.000***	-0.000***	-0.000***	-0.000***
	(-33.845)	(-17.039)	(-21.795)		(-36.064)	(-35.086)	(-26.885)	(-44.546)
total population	0.042***	-0.274***	0.198***	0.120***	-0.040***	0.025**	0.076***	-0.112***
	(3.807)	(-13.501)	(15.374)	(2.657)	(-3.025)	(2.126)	(6.792)	(-10.534)
population 65+	-0.044***	-0.015***	-0.065***	-0.038***	-0.044***	-0.044***	-0.042***	-0.056***
	(-15.322)	(-2.890)	(-19.668)	(-3.399)	(-13.503)	(-14.433)	(-14.334)	(-20.142)
population density	0.248***	0.141***	0.302***	0.242***	0.235***	0.202***	0.256***	0.195***
	(31.604)	(11.512)	(29.997)	(7.547)	(25.652)	(22.011)	(30.952)	(24.572)
temperature	-0.047***	-0.021***	-0.068***	-0.036***	-0.048***	-0.048***	-0.045***	-0.065***
	(-29.842)	(-7.653)	(-38.443)	(-4.789)	(-28.314)	(-28.339)	(-27.948)	(-45.500)
rainfall	-0.011	0.169***	-0.107***	0.015	0.018	-0.008	-0.023**	-0.008
	(-1.004)	(10.080)	(-8.433)	(0.295)	(1.547)	(-0.678)	(-2.139)	(-0.693)
GDP per capita	1.050***	0.689***	1.248***	1.185***	0.983***	1.019***	1.053***	1.106***
	(53.821)	(24.127)	(51.659)	(14.868)	(47.368)	(51.841)	(54.738)	(57.816)
Gini coefficient	0.046***	0.009***	0.073***	0.019**	0.051***	0.049***	0.047***	0.055***
	(23.688)	(2.960)	(32.457)	(2.208)	(24.953)	(24.787)	(24.040)	(28.179)
international visitors	-0.031**	0.031	-0.072***	0.060	-0.068***	-0.024*	-0.022	-0.036***
	(-2.349)	(1.591)	(-4.222)	(0.969)	(-4.789)	(-1.722)	(-1.595)	(-2.804)
international trade	-0.064***	0.173***	-0.189***	0.106**	-0.023**	-0.040***	-0.123***	-0.050***
	(-6.417)	(9.062)	(-20.352)	(2.392)	(-1.982)	(-3.580)	(-9.837)	(-5.431)
health expenditure	0.066***	-0.005	0.113***	0.062***	0.048***	0.073***	0.084***	0.053***
	(11.322)	(-0.500)	(19.302)	(2.663)	(7.007)	(11.437)	(13.894)	(9.550)
hospital beds	-0.265***	-0.173***	-0.330***	-0.211**	-0.254***	-0.255***	-0.255***	-0.384***
	(-12.397)	(-5.052)	(-12.055)	(-2.178)	(-11.185)	(-11.712)	(-11.778)	(-19.243)
SARS outbreak	-0.284***	-0.563***	-0.212***	0.047	-0.401***	-0.439***	-0.250***	-0.101***
	(-8.634)	(-9.378)	(-5.577)	(0.336)	(-11.218)	(-12.357)	(-7.420)	(-3.337)
government expenditure	0.026***	0.039***	0.022***	0.040***	0.031***	0.031***	0.023***	0.032***
	(9.524)	(8.279)	(6.996)	(3.550)	(10.476)	(10.789)	(8.223)	(12.097)
government effectiveness	-0.809***	-0.502***	-1.017***	-0.978***	-0.792***	-0.863***	-0.784***	-0.922***
	(-31.429)	(-11.093)	(-34.794)	(-8.432)	(-28.262)	(-31.295)	(-29.672)	(-37.893)
rest of world infection	0.298***	0.463***	0.839***	1.112***	0.493***	0.507***	0.779***	0.258***
	(7.581)	(15.958)	(13.589)	(9.450)	(18.877)	(19.050)	(30.240)	(13.441)
test ratio	0.346***	0.221***	0.406***	0.371***	0.362***	0.348***	0.353***	0.253***
	(40.566)	(16.489)	(39.921)	(9.656)	(39.851)	(39.695)	(41.059)	(31.690)
Number of observations	17,285	6,625	10,660	700	16,136	16,757	17,060	14,681
R-squared	0.800	0.744	0.687	0.744	0.784	0.784	0.800	0.751

Notes:

1. t-values are reported in parentheses. The stars *, ** and *** indicate the significance at 10%, 5% and 1%, respectively.
2. Days stands for the number of days since first infection case except for column (8).
3. Column (1) reports results adding monthly dummies.
4. Columns (2) and (3) report results for subsamples during Jan-April and May-Aug 2020, respectively.
5. Column (4) reports results using a subsample of observations in the 11th week since the first infection case.
6. Column (5) reports results excluding countris with population less than 2 million.
7. Column (6) reports results excluding countris with population density larger than 1,000 people per square kilometer.
8. Column (7) reports results excluding China in the sample.
9. Column (8) resports results using observations since first 50 infection cases, instead of the first case.

Table 6 Robustness Checks for Deaths Regressions

Dependent variable	log of deaths per million population							case fatality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
sample	Dummy	Jan-April	May-Aug	11th Week	Pop. 2M+	Density 1K-	no China	TOP25
Days	0.044***	0.082***	0.038***		0.042***	0.041***	0.033***	0.126***
	(38.570)	(38.156)	(26.403)		(42.868)	(41.950)	(32.639)	(8.335)
$Days^2$	-0.000***	-0.001***	-0.000***		-0.000***	-0.000***	-0.000***	-0.000***
	(-24.244)	(-19.331)	(-17.482)		(-33.399)	(-33.534)	(-24.317)	(-10.739)
total population	0.136***	-0.168***	0.227***	0.218***	0.128***	0.106***	0.134***	0.784***
	(12.757)	(-11.292)	(17.187)	(4.626)	(10.658)	(9.868)	(11.744)	(11.345)
population 65+	0.007**	0.014***	0.004	0.016	0.008***	0.008***	0.012***	0.161***
	(2.484)	(2.929)	(1.143)	(1.260)	(2.706)	(2.859)	(4.178)	(4.620)
population density	0.216***	0.183***	0.223***	0.237***	0.192***	0.265***	0.205***	0.724***
	(25.132)	(15.518)	(20.824)	(6.117)	(20.291)	(27.538)	(23.487)	(14.929)
temperature	-0.071***	-0.044***	-0.082***	-0.074***	-0.065***	-0.066***	-0.069***	-0.110***
	(-46.601)	(-20.669)	(-44.898)	(-11.250)	(-41.287)	(-44.369)	(-44.714)	(-23.915)
rainfall	0.067***	0.167***	0.024*	0.069	0.071***	0.059***	0.051***	2.770***
	(6.043)	(10.719)	(1.789)	(1.405)	(6.114)	(5.332)	(4.550)	(15.694)
GDP per capita	0.724***	0.440***	0.816***	0.869***	0.725***	0.759***	0.789***	0.267
	(39.128)	(13.955)	(37.857)	(12.644)	(38.908)	(40.669)	(42.902)	(0.884)
Gini coefficient	0.035***	-0.006**	0.052***	0.036***	0.028***	0.034***	0.032***	-0.016
	(20.209)	(-2.542)	(25.368)	(5.023)	(15.287)	(19.607)	(18.248)	(-1.138)
international visitors	0.112***	0.069***	0.118***	0.142***	0.137***	0.125***	0.097***	0.035
	(9.629)	(3.983)	(8.431)	(2.886)	(11.257)	(10.195)	(8.277)	(0.298)
international trade	-0.112***	0.065***	-0.173***	-0.119***	-0.066***	-0.077***	-0.019	0.086**
	(-13.404)	(5.488)	(-17.184)	(-3.347)	(-7.899)	(-9.651)	(-1.635)	(2.035)
health expenditure	0.167***	0.068***	0.208***	0.181***	0.175***	0.161***	0.148***	0.216***
	(36.623)	(8.983)	(40.774)	(10.010)	(33.134)	(33.429)	(29.118)	(5.591)
hospital beds	-0.741***	-0.733***	-0.752***	-0.814***	-0.771***	-0.720***	-0.728***	-3.562***
	(-35.645)	(-24.226)	(-28.856)	(-8.356)	(-35.441)	(-33.469)	(-34.099)	(-22.950)
SARS outbreak	0.100***	0.114**	0.061	0.172	0.131***	0.184***	0.100***	-0.966***
	(3.265)	(2.556)	(1.617)	(1.181)	(4.272)	(5.901)	(3.192)	(-3.459)
government expenditure	0.020***	0.035***	0.013***	0.038***	0.021***	0.015***	0.018***	0.118***
	(8.250)	(9.267)	(4.410)	(3.606)	(8.115)	(6.002)	(7.337)	(4.225)
government effectiveness	-0.893***	-0.663***	-0.980***	-1.039***	-0.981***	-0.903***	-0.955***	-3.671***
	(-34.826)	(-15.130)	(-32.944)	(-9.705)	(-36.992)	(-35.067)	(-37.348)	(-25.706)
rest of world infection	0.068**	0.134***	-0.104**	-0.044	0.189***	0.209***	0.338***	-1.785***
	(2.575)	(7.881)	(-2.494)	(-0.363)	(11.510)	(12.265)	(19.729)	(-4.154)
test ratio	0.175***	0.141***	0.190***	0.224***	0.192***	0.172***	0.167***	
	(21.531)	(10.162)	(19.877)	(6.758)	(23.382)	(21.518)	(21.050)	
Number of observations	14,119	4,097	10,022	658	13,292	13,692	13,901	3,793
R-squared	0.694	0.704	0.647	0.674	0.689	0.688	0.687	0.479

Notes:

1. t-values are reported in parentheses. The stars *, ** and *** indicate the significance at 10%, 5% and 1%, respectively.
2. Days stands for the number of days since first death case.
3. Column (1) reports results adding monthly dummies.
4. Columns (2) and (3) report results for subsamples during Jan-April and May-Aug 2020, respectively.
5. Column (4) reports results using a subsample of observations in the 11th week since the first infection case.
6. Column (5) reports results excluding countris with population less than 2 million.
7. Column (6) reports results excluding countris with population density larger than 1,000 people per square kilometer.
8. Column (7) reports results excluding China in the sample.
9. Column (8) resports results using CFR as dependent variable and a subsample of 25 countries with the hightest test ratio.

Data Appendix

The data used in this study are all collected from official sources that are publicly available. Our explanatory variables include six categories: demographic conditions, geographic conditions, economic conditions, global interdependency, healthcare conditions and public governance. This data appendix provides a detailed definition and data source of these variables.

Demographic conditions

Total population

The World Bank provides us the midyear estimate of the total population in 2018, which are combined from the United Nations Population Division and Census reports of different national statistical offices. All residents, regardless of legal status or citizenship, belong to the total population of each country. We fill in any missing value of the total population in 2018 with the latest value we can obtain from the same source in an early year. The same procedure is applied to all the other explanatory variables if missing values arise to ensure the data integrity.

Population 65+

Population65+ is calculated by taking the ratio of the population age 65 and above to the total population. The definition of the total population is discussed above, while the population age 65 and above is offered by the World Bank. The World Bank staff estimates the total population age 65 and above by using the source of age/sex distributions of the United Nations Population Division's World Population Prospects: 2019 Revision. The latest data is for 2018, and we fill in the missing value with the latest value we can obtain.

Population density

To reduce measurement error, we use land area instead of the territorial area to calculate population density. The World Bank provides land area (sq.km) in 2018, which excludes area under inland water bodies, national claims to continental shelf, and exclusive economic zones, collected by the Food and Agriculture Organization (FAO) of the United Nations through annual questionnaires. Population density is the total population divided by land area in square kilometers.

Geographic conditions

Temperature, rainfall

Temperature and rainfall are provided by the Climate Change Knowledge Portal, a portal under the World Bank to comprehensive country data related to climate change. We use the average temperature (℃) and average rainfall (mm) across countries in March 2016 as proxies of temperature and rainfall during the pandemic of COVID-19. The data for 2016 is the latest data available on the website, and climate change is not significant in just a few years. Besides, the COVID-19 is characterized as a pandemic by WHO in March. Thus, we believe the data of March 2016 are reasonable proxies.

Economic conditions

GDP per capita

The World Bank provides GDP across countries in 2018, which is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Data are in current U.S. dollars. GDP per capita is GDP divided by the total population we defined above.

Gini coefficient

Based on primary household survey data of the most recent year, the World Bank constructs the Gini coefficient, measuring the degree of inequality in a distribution. The Gini coefficient is the ratio of the area between the Lorenz curve and a hypothetical line of absolute equality over the total area under the hypothetical line of absolute equality. Thus a Gini coefficient of 0 implies perfect equality, while a coefficient of 100 implies perfect inequality.

Global interdependency

International visitor

Collected data from the World Tourism Organization, the World Bank provides us with the number of international inbound tourists in 2018. International inbound tourists refer to people who travel to a country other than their usual residence and usual environment for a period not exceeding 12 months. Also, the primary purpose of this travel is other than an activity remunerated from within the country visited. The international visitor variable in our study is normalized by taking the natural logarithm of international visitors per million people.

International trade

Using the import and export of goods of each country in 2018 provided by United Nations Comtrade, we construct a measure of global interconnectedness. We start with a matrix where the first row is filled country 1's import from and export of goods to country 2, 3, 4, and so on, respectively. The rest rows have a similar definition. The diagonal of the matrix, which is the country's import and export of goods to itself, is 0. Then we normalize this matrix from absolute values into shares of import and export of each country, using its total import and export to the rest of the world. For data in row i and column j, it measures the effect on the country i from each country j. International trade is calculated by summing up all the shares in one column, let's say column j. It measures the weighted interconnectedness of country j with respect to the rest of the world. Ideally, this measure should be based on by-country international passengers from a country and into a country. However, such information is not publically available. Thus we use the by-country import and export of goods as an alternative.

Healthcare conditions

Health expenditure

The World Bank provides us with current health expenditure expressed as a percentage of GDP in 2017, which stems from the WHO Global Health Expenditure Database. Estimates of this variable include the consumption of healthcare goods and services during each year but exclude capital health expenditures such as buildings, machinery, IT, and stocks of vaccines for emergencies or outbreaks.

Hospital beds

The information of hospital beds per 1,000 people is offered by World Bank who supplement WHO's original data by country data. The latest data available is for 2015, with massive missing values. Thus, a large amount of data is supplemented by data in the previous years, such as 2013 or 2014. Hospital beds include inpatient beds that can be used in public, private, general, and specialized hospitals and rehabilitation centers. In most cases, this also includes emergency and chronic beds.

SARS outbreak

SARS outbreak is a dummy variable, which equals one if the country reported probable cases of SARS in 2003. The source is collected from Cumulative Number of Reported Probable Cases of Severe Acute Respiratory Syndrome (SARS), reported by WHO.

Public governance

Government expenditure

Government expenditure refers to the ratio of general government final consumption expenditure to GDP. It includes most government and security expenditures such as the purchases of goods and services, compensation of employees, and expense of national defense and security. However, it excludes government military expenditures that are part of government capital formation. We collect the source in 2018 from the World Bank database.

Government effectiveness

The Worldwide Governance Indicators provide us with government effectiveness updated to 2018. The range of this variable is from approximately -2.5 (weak) to 2.5 (strong). Estimates of government effectiveness reflect the performance of government in the following field: (1) the quality of public services; (2) the quality of civil services and the degree of its independence from political pressures; (3) the quality of policy formulation and implementation; (4) the credibility of the government's commitment to such policies.

Additional controls

Rest of world infection

Since we have the number of infection of COVID-19 for each country on a daily basis from WHO, we construct the rest of world infection relative to a country by calculating cumulative infection cases of COVID-19 excluding the country itself.

Test ratio

We download the total COVID-19 test performed by country from the Humanitarian Data Exchange (HDX), who compiles sources from different government databases and only updates from time to time. At the moment of our current empirical exercises, which is 15 May, the most recent complete data for our country list is up to 22 April. We use this latest test data of each country to construct the time-invariant test ratio. The test ratio in our paper is normalized by taking the natural logarithm of total test per million people.