MAGKS

Göttingen · Kassel · Aachen · Siegen · Marburg · Gießen

Joint Discussion Paper Series in Economics

by the Universities of

Aachen · Gießen · Göttingen Kassel · Marburg · Siegen

ISSN 1867-3678

No. 50-2020

Jenny Bethäuser and Jennifer Muschol

The Die is Cast – Factors Influencing Mortality during the COVID-19 Pandemic

Coordination: Bernd Hayo • Philipps-University Marburg
School of Business and Economics • Universitätsstraße 24, D-35032 Marburg
Tel: +49-6421-2823091, Fax: +49-6421-2823088, e-mail: hayo@wiwi.uni-marburg.de

The Die is Cast - Factors Influencing Mortality during the COVID-19 Pandemic *†

Jenny Bethäuser‡
jenny.bethaeuser@wi.jlug.de

Jennifer Muschol§
jennifer.muschol@wi.jlug.de

July 15, 2020

Abstract

Since the beginning of the year, almost the entire world has been thrown off course by the outbreak of the COVID-19 pandemic, which has caused health, social and economic challenges. In an international comparison it can be seen that the mortality rates vary widely between countries. This study therefore aims to investigate the quality of international healthcare systems and their potential risk factors in order to explore the differences in mortality. After the derivation of suitable variables and the collection of a widespread data set, we were able to detect with six different OLS regressions that the mortality rate significantly decreases with a higher number of hospital beds and increases with a higher proportion of elderly population ($p < 0.05$ respectively). This work also succeeded in partly explaining the varying international COVID-19 mortality rates with an already existing health economic index (adj. $R^2 = 28.4\%$) and an own set of variables (adj. $R^2 = 27.7\%$). The association of the quality of healthcare systems as well as risk factors with COVID-19 mortality rates might provide important implications for future policy decisions.

Keywords: *COVID-19; Coronavirus; Cases; Deaths; Pandemic; Mortality; Healthcare System; Health Economics*

JEL Classification: *C12; C13; I1; I15.*

Data Accessibility: *The data set generated and analyzed during this study is available from the corresponding author on reasonable request.*

*Both authors contributed equally to this work.

†We thank Prof. Peter Winker and Prof. Christian Gissel for fruitful comments.

‡Chair for Statistics and Econometrics, Department of Economics, Justus Liebig University Giessen, Germany.

§Chair for Health Economics, Department of Economics, Justus Liebig University Giessen, Germany.

I Introduction

The new decade has not really started yet and the world is already in turmoil. The novel coronavirus (SARS-CoV-2) that causes the disease COVID-19 is keeping almost the entire world in suspense. Since the first reported outbreak in China on December 8, 2019, the coronavirus has been spreading rapidly worldwide (Hu et al. 2020; WHO 2020c).

The world map of the Johns Hopkins University (JHU) shows that the number of countries affected by COVID-19 is continuously increasing together with worrying consequences (JHU 2020). Since March 11, 2020 the World Health Organization (WHO) classifies COVID-19 as a pandemic due to the increasing number of cases (WHO Europe 2020c). In addition to high disease rates in some countries, hundreds of thousands of people have died worldwide as a result of the new kind of virus. Meanwhile there are 9.237.812 total confirmed cases and 483.344 global deaths reported by JHU 2020 (effective June 24, 2020). Normal life has come to a standstill in many countries, as school closures, lockdowns and other public sanctions have been introduced in an attempt to control the spread of COVID-19. As a result of temporarily or permanently closed businesses, dismissed employees or employees in home offices, not only health is threatened by the virus, also social structures and the economy are being vastly affected (Nicola et al. 2020).

In order to counter COVID-19 and its effects in the best possible way, research on this topic has risen intensely. There is much speculation as to why the number of deaths varies so much in different countries (Cummings et al. 2020; Docherty et al. 2020; Guan et al. 2020; Petrilli et al. 2020; Wang et al. 2020; Yang et al. 2020). The probability of dying from COVID-19 could depend on individual risk factors as the quality of medical care and much broader, general demographic, economic, political and healthcare system related factors in the different countries. Previous research has pointed out that the number of physicians and hospital beds in a country, risk factors as an increased age or economic power, out of pocket payments (OOPs), the quality of care for other diseases such as influenza and the number of tests might play an important role among others regarding mortality (Docherty et al. 2020; Ghosal et al. 2020; Jüni et al. 2020; Lippi et al. 2020; Nap et al. 2007; Roy and Khalse 2020; Rudge et al. 2012; Sarmadi et al. 2020; Sathyabhama and Suresh 2020; Sobieraj et al. 2007; Viboud et al. 2016; Weissman et al. 2020; WHO Europe 2020b). The aim of our study is to analyze the influence of these different indicators in explaining the varying COVID-19 mortality rates between countries worldwide.

Our contribution to the field of research is to further investigate the overall impact of the quality of the healthcare systems on the COVID-19 mortality for the following purposes: 1) To find an at least partial explanation for the large differences in mortality rates in the worldwide comparison. 2) To give different stakeholders e.g. policy makers, insights into potential provisions for future pandemic outbreaks. 3) To provide a theoretical framework for further research.

II Methods and Data

To further empirically investigate the above-mentioned factors and their influence on mortality, they need to be operationalized. One possibility is to work with already existing health economic indices. A widely used is the Health Access and Quality Index (HAQI) (Global Burden of Diseases Study 2016 Healthcare Access and Quality Collaborators 2018): Based on updated estimates from the Global Burden of Disease Study 2016, HAQI collaborators have used 32 causes of death to create their index in order to approximate access to and quality of personal healthcare. In effective healthcare, none of the 32 causes should result in death. The authors transformed each cause of death to a scale with 0 being the first (worst) percentile observed between 1990 and 2016 and 100 being the 99th (best) percentile. The greatest strength of the HAQI is that it wraps what is often considered to be immeasurable into a metric that approximates personal access to healthcare and its quality in the individual countries. The HAQI mainly relates medically preventable causes of death to the prevailing health system in the respective countries (Global Burden of Diseases Study 2016 Healthcare Access and Quality Collaborators 2018).

However, a second Index, namely the Global Health Security Index (GHSI) established by the JHU has recently become more widely known through the media and focuses especially on the ability of each country to cope with pandemics and epidemics (Nuclear Threat Initiative et al. 2020; Bell 2020): The GHSI presents the results of a worldwide survey in 195 countries. The survey was conducted by the Center for Health Security at Johns Hopkins University, the Nuclear Threat Initiative and the Economist Intelligence Unit. The index is based on a questionnaire with 140 questions in six categories to assess a country's capability to prevent and mitigate epidemics and pandemics. The answers to the questions are compiled exclusively from open source materials. The researchers worked with an international advisory panel of 21 experts from 13 countries to answer the questions. According to the authors, the Index shows that no country in the world is 100% prepared for epidemics and pandemics. (Nuclear Threat Initiative et al. 2020)

Nevertheless, another way to operationalize the factors that might influence mortality is to manually select and combine several individual variables that fit the considerations in the previous section. We used data from official sources such as the WHO (WHO 2020a, 2020b; WHO Europe 2020a), the Organisation for Economic Co-operation and Development (OECD) (OECD 2020b, 2020c, 2020d, 2020e), Eurostat (Eurostat 2020), Our World in Data (Roser et al. 2020) and the World Bank (The World Bank 2020).

For individual risk factors in the context of medical care, physician density and the number of hospital beds each per 1,000 inhabitants were chosen as quantity measures. The quantity of treatment can be determined by the number of physicians as they ensure that patients are cared for adequately, which is especially important in an exceptional situation like a pandemic. In addition to the personnel, the infrastructure, in particular the number of hospital beds, determines how many severe cases can be treated at the same time. For quality measures, we used the potential years of life lost (PYLL) per 100,000 inhabitants due to influenza for patients over 75 years. COVID-19 is unprecedented in this form, but COVID-19 and influenza are both common respiratory viral infections (Itaya et al. 2020). The PYLL are an indicator for deaths that may have been preventable and therefore might be able to reflect the quality of treatment in the healthcare system (OECD 2020f).

The data for *PhysiciansDensity* was derived from the OECD as the total number of practicing physicians per 1,000 population from 2018 or latest available. The OECD states that for some countries physicians have been added which are not directly involved in patient care but are active in the health sector (OECD 2020c). We completed this data set with the most current rescaled data from the WHO (WHO Europe 2020a). The data for *HospitalBeds* was obtained from the OECD and was completed with rescaled data from the WHO as well (OECD 2020e; WHO 2020a). For *PYLLInfluenza* the OECD is the source of the data set and again the latest available year was considered (OECD 2020d).

General risk factors to which people are exposed throughout their lives are more diverse. The per capita gross national income (GNI) in current US$ was used as a proxy for the economic prosperity of a country, since it is decisive for how much money a country can raise to cope with a pandemic (OECD 2020a). The percentage of the population 80 years or older was used as a measure of demographic development. It is already detected that particularly older people often suffer a more severe course of COVID-19 disease due to pre-existing comorbidities and are therefore more at risk to die (Docherty et al. 2020). Health policy and thus the financing of healthcare in a country could also be decisive. In this context OOPs are a critical factor since they are payments that healthcare providers obtain from patients directly when a service is provided and that are not covered by insurance. They pose a risk because patients avoid necessary medical services for financial reasons (United Nations Department of Economic and Social Affairs 2019). OOPs as a percentage of total health expenditures are therefore considered. Nevertheless, health policy also affects how a country deals with a pandemic. For example, this can be seen in the number of tests carried out. The more people are tested, the better the outbreak of the pandemic can be controlled. The total number of tests within 30 days after the 50^{th} death scaled down to 100,000 inhabitants was therefore utilized.

The data for *GNIperCapita* for the most recent year in the respective countries was derived from the World Bank which refers to the World Bank and OECD national accounts data files as source. The values are normalized to US dollars, which lessens the effect of exchange rate fluctuations (The World Bank 2020). The data for *Population80* as the percentage share of the population 80 years or older in the respective countries was obtained from the OECD for 2018 and supplemented by Eurostat for 2019 (OECD 2020b; Eurostat 2020). For *OOPs* as a percentage of total health expenditure the latest available data set from 2017 by the WHO was used (WHO 2020b). For the *NumberofTestsIn30Days* the number of tests on the first day with a minimum of 50 reported deaths was subtracted from the number of tests on the thirtieth day after the 50^{th} reported deaths per 100,000 inhabitants. We received the number of tests from Our World in Data and in case of missing values for specific days, we interpolated them. Furthermore, the countries partly reported numbers in different units such as tests performed, people tested or even unclear units (Roser et al. 2020).

COVID-19 mortality can be operationalized in two different ways. Besides the number of people infected or tested, the JHU reports the absolute number of deaths per country (JHU 2020). We will seek to correct known distortions in the data collection. First, the absolute figures are scaled to 100,000 inhabitants to compensate for the difference between populous and poorly populated countries (United Nations Department of Economic and Social Affairs 2019). Furthermore, the dynamics of the pandemic must be considered. In order to make the countries comparable over time, we use a uniform time period of 30 days after the 50^{th} reported death. The starting point of the 30 days is not the first reported COVID-19 death to compensate potential biases in the early documentation of deaths. For the sake of simplicity this first dependent variable as proxy for the COVID-19 mortality is abbreviated to *RelativeNumberofDeaths* in the following regressions.

A second way to approximate the mortality is to include the number of tests to take the different international testing approaches into account (Roser et al. 2020). With more tests, more infected people and deaths are reported. But of course, also more people who are not yet infected. The total number of tests within 30 days from the 50^{th} death scaled down to 100.000 inhabitants was considered as the *RelativeNumberofTests*. The *RelativeNumberofDeaths* from the first approach was then divided by the *RelativeNumberofTests* to measure how high the mortality rate is among those tested. The numbers in the numerator and denominator are the increase in deaths and tests from the same period 30 days after the 50^{th} death. This mortality rate is abbreviated as *DeathsPerTests* in the following regressions.

Based on the data set composed until June 24, 2020 (summary shown in Table 1), we will estimate a total of six different regression models with Ordinary Least Squares (OLS): The two mortality variables *RelativeNumberofDeaths* in table 2 and *DeathsPerTest* in table 3 on each of both health indices (HAQI and GHSI) and on our self-assembled set of variables. As a robustness check, we especially examined the models with our own set of variables over time in table 4 and 5and tested a model with a modified dependent variable, namely the relative number of tests within 60 days after the 50^{th} death (Table A.1).

Table 1: Data Set

	Dependent Variables:		*Explanatory Variables:*			
	RelativeNumber ofDeaths	DeathsPer Tests	HAQI	GHSI	Population 80	Hospital Beds
Min	0.080	0.0002	19.000	16.200	0.8%	0.100
Mean	2.280	0.0032	67.000	40.100	4.1%	2.155
Max	66.108	0.0477	97.000	83.500	8.8%	13.050

	Explanatory Variables:				
	Physicians Density	PYLL Influenza	GNIper Capita	OOPs	NumberTests In30Days
Min	0.320	0.000	390.000	2.99%	16.918
Mean	3.210	5.500	6 395.000	31.79%	765.999
Max	506.130	22.000	116 430.000	84.35%	5658.728

III Results

First, the relationship between the *RelativeNumberofDeaths* and the HAQI was investigated using a simple OLS model (Table 2, column 1). However, from the original data set of 178 countries, only 83 countries have so far reported the HAQI in combination with the *RelativeNumberofDeaths* until the cut-off date. This sample includes 33 European countries, 20 from Asia, 14 from Africa, 8 from North and Central America, 7 from South America and 1 from Australia.

A non-linear correlation between the *RelativeNumberofDeaths* and the HAQI seems plausible: The direction of the effect might differ between well-positioned countries in the HAQI and badly-positioned ones, which is why a quadratic form was used for estimation. This was also confirmed by the RESET test. The output (Table 2, column 1) shows that the HAQI in simple and squared form has a statistically highly significant influence on the *RelativeNumberofDeaths*. A country that rises by one unit in the HAQI can expect 0.699 fewer deaths per 100,000 inhabitants within the 30 days after the 50^{th} death ceteris paribus (c.p.). This negative effect initially becomes smaller, then reverses and becomes positive when HAQI values increase above 50. This means that in countries with better healthcare systems a higher number for *RelativeNumberofDeaths* has to be recorded.

The adjusted R^2 shows that about 28.4% of the variation in the *RelativeNumberofDeaths* can be explained by fluctuations in the HAQI. Since heteroscedastic error terms are present, the initially reported significance cannot be counted as such. In table 2, the corrected significances are shown with are calculated with the help of heteroskedasticity adjusted standard errors. The residuals are not autocorrelated and not normally distributed. Since our data set is not too small and the residuals in the histogram look close to normal distributed, we assume that the t-values of the tests are still valid.

Table 2: OLS Models for Relative Number of Deaths

	Dependent variable:		
	RelativeNumberofDeaths		
	(1)	(2)	(3)
HAQI	-0.706^{**}		
	(0.290)		
I(HAQI^2)	0.007^{***}		
	(0.002)		
GHSI		-0.224	
		(0.473)	
I(GHSI^2)		0.004	
		(0.005)	
HospitalBeds			-1.350^{**}
			(0.590)
Population80			289.338^{**}
			(116.278)
PhysiciansDensity			-0.635
			(1.873)
GNIperCapita			0.0001
			(0.0001)
Constant	15.755^{*}	6.464	1.290
	(8.674)	(11.474)	(4.552)
Observations	83	83	43
R^2	0.302	0.063	0.346
Adjusted R^2	0.284	0.040	0.277
Residual Std. Error	9.060 (df = 80)	10.494 (df = 80)	9.049 (df = 38)
F Statistic	17.282^{***} (df = 2; 80)	2.689^{*} (df = 2; 80)	5.018^{***} (df = 4; 38)
Note:			*p<0.1; **p<0.05; ***p<0.01

In addition to the HAQI we examine the relationship between the GHSI and the *RelativeNumberofDeaths* (Table 2, column 2). The data set again contains 83 countries. For better comparability and by theoretically assuming a nonlinear relationship between HAQI and the *RelativeNumberofDeaths* in the first regression, the relationship between GHSI and the *RelativeNumberofDeaths* is modelled with a quadratic equation as well. The output in table 2, column 2 shows no significant effects, although the signs of the coefficients correspond to those of the estimation with the HAQI. The residuals are exemplary, besides deviating from the normality assumption. Bootstrapping of the residuals leads only to small changes of the standard errors. The adjusted R^2 is low at 4%, so that it can be assumed that the ranking of the GHSI has almost no information about how many deaths a country has to report in the event of a pandemic.

Besides already existing and pooled indices, we aimed to explain the variance in the *RelativeNumberofDeaths* with a set of manually selected individual variables (*HospitalBeds*, *Population80*, *PhysiciansDensity*). Some countries do not report values for all explanatory variables. This reduces the data set to 27 European, 9 Asian, 3 North and Central American, 2 South American, 1 African and 1 Australian country, i.e. a total of 43 countries.

The first coefficient in the output (Table 2, column 3) besides the constant shows a highly significant ($p < 0.05$) and negative correlation between the number of *HospitalBeds* and the *RelativeNumberofDeaths*. In other words, if one more hospital bed is available per 1,000 inhabitants, the *RelativeNumberofDeaths* decreases c.p. by 1.35 per 100.000 inhabitants. Since COVID-19 is a viral disease, in which people with a severe course are dependent on medical care in hospitals and in the intensive care units, this correlation is plausible.

The coefficient indicating the correlation between the proportion of the population over 80 years and the *RelativeNumberofDeaths* is significant ($p < 0.05$) as well and has a positive sign. Societies whose population over 80 is growing by one percentage point can expect c.p. an increase in the *RelativeNumberofDeaths* by 289 per 100,000 inhabitants. Ageing societies are more at risk, as the immune system of the elderly is often already weakened and many have other comorbidities that foster death. The following two coefficients are not statistically different from zero, but the direction of the effects is nevertheless apparent. One more physician per 1,000 inhabitants lowers the *RelativeNumberofDeaths* c.p. and the coefficient of the per capita GNI shows a slightly positive correlation. However, the number that is of most interest is the adjusted R^2. It is shown that the manually selected variables can explain 27.7% of the variation in the *RelativeNumberofDeaths*, clearly outperforming the naive model with the GHSI as sole explanatory variable in column 2 (adj. $R^2 = 4\%$). It also approaches the explanatory content of the model with HAQI as a single explanatory variable in column 1 (adj. $R^2 = 28.4\%$).

As a robustness check we calculated the *RelativeNumberofDeaths* within 60 days for 40 of the 43 countries used in the 30-day model. The estimate does not change essentially (see Appendix A.1), apart from the effects that can be anticipated due to a longer observation period. The two significant variables become more precise and larger in absolute terms. The insignificance of all other variables remains unchanged and the adjusted R^2 increases only slightly to 30.7%.

A second way to approximate the mortality caused by the COVID-19 will be considered in the following table 3. By including the number of tests, the dependent variable is a mortality rate in % called *DeathsPerTests*. In the first attempt to regress the indices HAQI and GHSI to the *RelativeNumberofDeaths* in table 2 we assumed that the possibility of more tests caused the quadratic effect. Now, we assume a purely linear relationship, since the number of tests is contained in the variable to be explained.

Table 3: OLS Models for Deaths per Tests

	Dependent variable:		
	DeathsPerTests		
	(1)	(2)	(3)
HAQI	0.0001		
	(0.0001)		
GHSI		0.0003	
		(0.0001)	
HospitalBeds			-0.003^{***}
			(0.001)
Population80			0.431^{**}
			(0.185)
NumberTestsIn30Days			-0.00000^{**}
			(0.00000)
OOPs			0.028
			(0.027)
PYLLInfluenza			−0.0001
			(0.0005)
PhysiciansDensity			−0.001
			(0.003)
Constant	0.003	−0.006	0.010
	(0.007)	(0.007)	(0.011)
Observations	58	58	32
R^2	0.012	0.080	0.404
Adjusted R^2	-0.006	0.063	0.261
Residual Std. Error	0.011 (df = 56)	0.011 (df = 56)	0.012 (df = 25)
F Statistic	0.655 (df = 1; 56)	4.844^{**} (df = 1; 56)	2.823^{**} (df = 6; 25)
Note:			*p<0.1; **p<0.05; ***p<0.01

Unfortunately, the HAQI and the GHSi are not able to sufficiently map the *DeathsPerTests* in table 3, column 1 and 2. The coefficients are not statistically significant and the adjusted R^2 is negligible low (-0.6% and 6.3%). The error terms behave exemplary off the normality assumption.

In an attempt to explain the mortality rate among those tested, we have again assembled our own set of variables in table 3, column 3. Compared to the first set of variables, the number of tests carried out in each country within 30 days is now one of the explanatory variables (*NumberofTestsIn30Days*). To ensure adequate testing in a country, fiscal support is needed (OECD 2020a), why per capita GNI was no longer included in the model to not duplicate the effect. In addition, *PYLLInfluenza* have been included. By increasing the number of tests, it is possible to distinguish more clearly between those who have died of COVID-19 and those who have died of other lung diseases such as influenza. The proportion of self-payers in each country was included as a variable (*OOPs*) as well, since fully insured patients are more likely to be tested, which has an impact on further treatment and thus on the death rates.

Table 4: OLS Results over Time for First Set of Variables

	Dependent variable:			
	RelativeNumberofDeaths			
	(1)	(2)	(3)	(4)
HospitalBeds	-1.687	-1.946^{*}	-1.921^{**}	-1.350^{**}
	(0.990)	(0.941)	(0.705)	(0.590)
Population80	470.699	338.300	443.267^{***}	289.338^{**}
	(394.503)	(199.427)	(143.202)	(116.278)
PhysiciansDensity	-2.735	-0.416	-0.908	-0.635
	(10.136)	(4.007)	(2.410)	(1.873)
GNIperCapita	0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Constant	5.752	2.431	0.247	1.290
	(15.917)	(8.373)	(5.600)	(4.552)
Observations	10	21	32	43
R^2	0.653	0.379	0.420	0.346
Adjusted R^2	0.375	0.224	0.334	0.277
Residual Std. Error	8.751	11.640	9.739	9.049
	(df = 5)	(df = 16)	(df = 27)	(df = 38)
F Statistic	2.348	2.440^{*}	4.880^{***}	5.018^{***}
	(df = 4; 5)	(df = 4; 16)	(df = 4; 27)	(df = 4; 38)
Note:				*p<0.1; **p<0.05; ***p<0.01

The number of *DeathsPerTests* could be estimated for 32 countries: 20 from Europe, 5 from Asia, 3 from North and Central America, 2 from South America and 1 each from Africa and Australia. The output in table 3, column 3 shows that an increase in the number of beds per 1,000 inhabitants by one leads c.p. to a reduction of 0.3% points in the mortality of those tested. This negative correlation is highly significant ($p < 0.01$). The proportion of the population over 80 years of age is positively correlated to the 5% significance level with the *DeathsPerTests*. If the proportion increases by 1% point, the mortality rate increases c.p. by 43.1% points. The coefficient on the number of tests within 30 days after the 50^{th} death is statistically significant to the 5% level and shows that 1,000 more tests reduce the mortality rate among those tested c.p. by 0.19% points. Since only a small part of the tested persons is ill, more healthy persons are detected with each new test and in addition not every ill patient dies from the consequences of COVID-19 why the correlation is negative. The results for physician density, OOPs and the number of PYLL due to influenza are not statistically different from zero. However, the direction of the effects seems plausible. In terms of the adjusted R^2, it is shown that this second set of variables comes very close to the approach with the first variable set (26.1% compared to 27.7%) and also to the model where the *RelativeNumberofDeaths* is solely explained by the HAQI ranking (28.4%). All other estimated models are clearly outperformed in terms of explanatory power.

Looking at all these results, it remains questionable to what extent the effects will persist or materialize as more data is added over time. To make this transparent for the data already collected, the results of the two approaches with variable sets over time are presented in table 4 and 5. Whenever about 10 new data points, i.e. countries, were available, the model was re-estimated and results were extracted (column 1 to 4 in Table 4 and column 1 to 3 in Table 5).

Table 5: OLS Results over Time for Second Set of Variables

	Dependent variable:		
	DeathsPerTests		
	(1)	(2)	(3)
HospitalBeds	−0.002	-0.003^{**}	-0.003^{***}
	(0.003)	(0.001)	(0.001)
Population80	1.591	0.389	0.431^{**}
	(1.303)	(0.262)	(0.185)
NumberTestsIn30Days	−0.00000	−0.00001	-0.00000^{**}
	(0.00002)	(0.00001)	(0.00000)
OOPs	0.074	0.035	0.028
	(0.145)	(0.051)	(0.027)
PYLLInfluenza	0.003	0.001	−0.0001
	(0.004)	(0.001)	(0.0005)
PhysiciansDensity	−0.017	0.0002	−0.001
	(0.024)	(0.005)	(0.003)
Constant	−0.023	0.005	0.010
	(0.091)	(0.022)	(0.011)
Observations	9	21	32
R^2	0.700	0.521	0.404
Adjusted R^2	-0.200	0.315	0.261
Residual Std. Error	0.019 (df = 2)	0.012 (df = 14)	0.012 (df = 25)
F Statistic	0.777 (df = 6; 2)	2.536^{*} (df = 6; 14)	2.823^{**} (df = 6; 25)
Note:			*p<0.1; **p<0.05; ***p<0.01

When estimating the *RelativeNumberofDeaths* (Table 4), it is remarkable that all coefficients have the same sign over time and that the number of beds per 1,000 inhabitants and the proportion of people older than 80 become significant as 30 countries are included in the estimation. No significance is yet shown for the coefficient of physician density, but a reduction in standard errors over time is clearly visible. This coefficient could become significant with more data added. For the per capita GNI, the direction and size of the effect remains the same. We would not expect significant coefficients, even with more available data. The adjusted R^2 remains roughly around 30%.

In the approach with the second variable set in table 5, which examines the *DeathsPerTests*, not that many data points are available yet, why only three different estimations were conducted. A similar scenario compared to table 4 can be seen for the coefficients for the number of beds per 1,000 inhabitants and the percentage share of the population older than 80 years. The coefficients have the same sign and become significant as more data points are added. The same applies for the added variable *NumberTestsIn30Days*. For *OOPs*, the direction of the effect remains positive over time but becomes less relevant. Since the standard error becomes smaller here as well, the parameter can be estimated more reliably with more data points. For *PYLLInfluenza* the standard error also decreases and causes the coefficient to change from positive to negative. The coefficient of *PhysiciansDensity* fluctuates strongly between negative and positive. Possibly both coefficients settle at zero and are therefore presumably not significant in the future.

IV Discussion

Compared to existing literature, there are some studies that follow the same explorative approach as we do. Ji et al. 2020 conducted their studyin the early phase of the coronavirus onset abd found a significant positive correlation between the mortality and the incidence of COVID-19. The authors therefore proposed that regional disparities in healthcare resource availability could be a reason for different mortality rates in Chinese provinces. This was the first evidence about a link between healthcare resources and mortality in the COVID-19 pandemic. Lai, Wang, Wang, Hsueh, et al. 2020 pursued this approach as well and correlated cases, deaths and the mortality rate between December 31, 2019 and February 29, 2020 for 57 countries with the HAQI and the Health Care Index (HCI) (Lai, Wang, Wang, Hsueh, et al. 2020; Numbeo 2020). The analysis showed a significant positive correlation between the incidence and HAQI as well as HCI. They have explained the positive correlation with the fact that better health systems are superior to detect positive cases. However, a significant correlation between the HAQI or HCI with the mortality rate or deaths could not be found. This could be partly explained by missing data for some countries (Lai, Wang, Wang, Hsueh, et al. 2020).

In a following study Lai, Wang, Wang, and Hsueh 2020 iterated the analysis with 93 countries and data until March 6, 2020 and again found a significant positive correlation between the disease incidence and HAQI as well as HCI. However, this study did not take mortality rate and deaths into account. Aitken et al. 2020 conducted a similar approach with the GHSI. They examined the potential association between the GHSI and different COVID-19 outcomes with data for 100 countries until April 11, 2020. Their generalized linear model showed among others a significant positive correlation between GHSI and the adjusted deaths per million people per day (Aitken et al. 2020). Compared to these studies that consider the impact of the HAQI und GHSI as we did, several months have passed and we were able to work with a more current and comprehensive data set. Furthermore, we have adjusted the collected data in the best possible way to eliminate existing biases and worked with other empirical methods than previous authors did.

The total interpretive structural modelling approach, used in the study from Sathyabhama and Suresh 2020 is another attempt to find potential factors that influence the COVID-19 pandemic. The authors of this study were able to identify 11 factors that influence COVID-19 incidence. They detected as we did, that older people are more threatened by the current pandemic (Sathyabhama and Suresh 2020).

With respect to former influenza pandemics, some studies tried to calculate and model the necessary amount of hospital beds and health workers for mild or severe courses of diseases (Nap et al. 2007; Sobieraj et al. 2007). Using this approach, Rudge et al. 2012 have been able to detect missing healthcare resources in terms of hospital beds and equipment, nurses and doctors that could lead to avoidable mortalities for six Asian territories in case of an influenza pandemic. Similar to these findings, we included *HospitalBeds* and *PhysiciansDensity* in our model to analyze, if the availability of these healthcare resources has an impact on the varying COVID-19 mortality rates and were able to confirm this for the number of *HospitalBeds* per 1,000 inhabitants.

A study in preprint from Ghosal et al. 2020 and another study from Roy and Khalse 2020 used similar variables as we did. Ghosal et al. 2020 calculated the correlation coefficient between COVID-19 infection rates, total deaths, gross domestic product (GDP), physicians, hospital beds and testing rates for six countries, whereas Roy and Khalse 2020 correlated for 11 countries the number of COVID-19 deaths and cases with critical-care beds, median age of population, number of COVID-19 tests, population density, urban population percentage and GDP expense on healthcare. They found a significant negative correlation between critical care beds and the fatality rate (Roy and Khalse 2020), which is similar to our findings. Nevertheless, our model considers, besides a combination of their variables in a modified form, more variables, adjusted explanatory variables, a much larger number of countries and goes beyond a pure correlation analysis.

Initially, we have expected to find a purely negative linear correlation between the health indices HAQI or GHSI and the *RelativeNumberofDeaths* in table 2 or the *DeathsPerTests* in table 3. We expected that countries that achieve high scores in the indices would have fewer deaths due to the pandemic. However, the correlation with the *RelativeNumberofDeaths* was assumed and tested to be quadratic. That means for well-positioned countries high values in the indices lead to a higher *RelativeNumberofDeaths*. This could be explained by better trained personnel and more testing capacity, which overall leads to more detected deaths. In comparison, the HAQI seems to be the more informative index to explain the *RelativeNumberofDeaths*.

We also expected a positive correlation between the proportion of the population older than 80 years and a negative correlation for the number of *HospitalBeds*, *PhysiciansDensity* and *GNIper-Capita* with the *RelativeNumberofDeaths* in table 2. The expectations for the first two explanatory variables have been met. The other effects were not significant, although the direction of effects shown was entirely in line with our expectations.

In the second set of variables, the *NumberTestsIn30Days* was integrated into the variable to be explained, which is why the explanatory variables were also adjusted. Again, we expected a negative correlation between the number of *HospitalBeds*, *PhysiciansDensity* and, in addition, the *NumberTestsIn30Days* with the *DeathsPerTests* in table 3. A positive correlation was expected for the share of the population over 80 years (*Population80*), the *OOPs* and *PYLLInfluenza*. The association between *HospitalBeds*, *NumberTestsIn30Days* and *Population80* could be confirmed empirically. All other coefficients were not significant, but the direction of effects was as expected. In conclusion it can be said that the fluctuations in the HAQI can explain about as much of the fluctuations in the *RelativeNumberofDeaths* as the first set of variables (see Table 2: adj. R^2 28.4% and 27.7%). Our self-derived second set of variables also scores quite well and can still explain 26.1% of the variation in the number of *DeathsPerTests*. All other models achieve very small values in terms of the adjusted R^2 (4% GHSI/*RelativeNumberofDeaths* in Table 2; -0.6% HAQI/*DeathsPerTests* in Table 3; 6.3% GHSI/*DeathsPerTests* in Table 3).

Thus, since the number of observations between 32 and 83 is still very limited, it is possible that some effects we analyzed could turn out significant at a later stage with more data available. For the data already collected, we have shown how the directions and magnitudes of the effects change if about 10 more countries were included in the estimation (see Table 4 and 5). Particularly remarkable is the coefficient of physician density in the estimation of the first set of variables, which might become significant in the future (Table 4). However, data availability is not the only limitation related to our study. The reporting of the data used, especially the number of deaths and tests reported, depends heavily on the healthcare system of the individual country and also on the stability of the respective political and economic system. Unfortunately, so far there is no indication of how many people died from COVID-19, but are not recorded because they are not tested. On the other hand, there are certainly some reported COVID-19 deaths, which died from influenza but with symptoms similar to COVID-19.

We are aware of this distortion in the data and therefore the results of our study should be interpreted with caution. As seen e.g. in the HAQI estimation (Table 2, column 1), there are two ways in which a near-perfect healthcare system can affect the number of deaths. There could be more observed deaths due to more trained medical staff and more tests performed, or fewer deaths due to good prevention and avoidance. The same applies to the density of physicians. More physicians can treat more patients and are presumably able to save them from death by curing them. Conversely, more physicians, through their expertise, also lead to more deaths that are proven to have died of COVID-19. As with any estimate, causality must not be inferred from correlation. A proven correlation can also contain contrary effects, one of which outweighs the other and thus determines the sign.

Another limitation can be found in the data set used for the explanatory variables. To consider the largest possible number of countries in our model, we have supplemented partially incomplete data sets from one data source with data sets from another source. At the same time, we have ascertained to use the most up-to-date data for each country. The data sets hence originate from various sources as well as different years and in some cases the data was collected using different methods. Despite a potential bias, we have chosen this approach to ensure that our sample does not become too small and is most recent for the respective countries. Nevertheless, it is important to remember that much has changed during the pandemic and that the considered variables are geared towards regular patient care while we are in an exceptional situation of a pandemic. In the meantime, several hospitals have increased their bed capacities and postponed non-essential operations to make room for COVID-19 patients as well (Australian Government 2020; Centers for Medicare & Medicaid Services 2020a). In addition, some countries are now paying for the treatment of COVID-19 (Centers for Medicare & Medicaid Services 2020b).

Caution is also required when considering estimates over time (see Table 4 and 5). Effects that are significant in small samples and no longer with more data added could have different causes. A learning effect could have set in, so that countries that are later affected by the COVID-19 pandemic were better prepared and could learn from early affected countries. Therefore, we have included the number of days between the outbreak of the virus and the 50^{th} reported death in each country in the models as a trial, but without seeing the desired effect. It remains interesting to see how these estimates will develop as the pandemic progresses and more data becomes available.

An important component that we have not included in the model are the non-pharmaceutical interventions that countries have implemented in very different ways and that have certainly had an effect on infection and death rates. However, the overall development of the pandemic is dynamic why it is neither possible nor appropriate to make definite statements about the future.

V Conclusion

The aim of this work was to investigate factors of health care systems in order to explain the often immense differences in mortality rates due to COVID-19 between countries worldwide. For this purpose, the *RelativeNumberofDeaths* and the *DeathsPerTests* were empirically investigated. Using the comprehensive health index HAQI, it can be shown that countries with a comparatively poorer outcome in the treatment of other diseases also have an increased COVID-19 mortality rate. Although HAQI is geared towards the normal state of healthcare systems and away from pandemics, it can explain mortality rates by COVID-19 well (see Table 2, column 1, adj. $R^2 = 28.4\%$).

The assumption that the available quantity and quality of treatment options plays a relevant role has been empirically confirmed as well (see Table 2, column 3, adj. $R^2 = 27.7\%$). In particular, the negative correlation between hospital beds and mortality from COVID-19 might give cause to reconsider the equipment of hospitals and improve it in the short term. Efficiency aspects may be an argument against such an investment, but especially in exceptional times of a pandemic there are direct and indirect costs as well as the resulting economic impact of infection and death from COVID-19 to be considered. In order to keep global death rates as low as possible, the cross-border use of health capacities might be helpful as well.

The assumption that the older population group in particular is contributing strongly to the rising death rates was empirically confirmed as well. Existing resources in the healthcare system should therefore aim to protect precisely this risk group and thus limit mortality rates.

Investments in testing capacity may be beneficial as well, not only to better assess the situation in each country and reduce the number of undetected cases of disease and death, but also to treat patients more specifically for COVID-19 and thus reduce mortality. A positive side-effect is that once people are identified as infected, they can be isolated and cannot infect others who might have died subsequently.

Our estimates give guidance in which countries the population and also politicians should be prepared for high mortality rates and how they could reduce them. However, it is not possible to predict the further spread of COVID-19 and when healthcare systems will be able to return to normal. Until then, everything possible should be done to stop the mortality rate from rising any higher. It should be noted that the GHSI, which is designed precisely for situations such as the COVID-19 pandemic, should not be used as a proxy for the expected death toll since it performs rather poorly (see Table 2, adj. $R^2 = 4\%$ and Table 3, adj. $R^2 = 6\%$).

Unfortunately, only in retrospect it will be possible to determine which countries have chosen the right strategy to keep deaths to a minimum.

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Appendix

A Outputs

Table A.1: Relative Number of Deaths for a period of 60 days

	Dependent variable:
	RelativeNumberofDeaths60
HospitalBeds	-3.178^{***}
	(1.034)
Population80	660.510^{***}
	(205.581)
PhysiciansDensity	-0.642
	(3.362)
GNIperCapita	0.00004
	(0.0001)
Constant	3.723
	(8.036)
Observations	40
R^2	0.378
Adjusted R^2	0.307
Residual Std. Error	15.642 (df = 35)
F Statistic	5.319^{***} (df = 4; 35)
Note:	*p<0.1; **p<0.05; ***p<0.01