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Decomposing Differences in Coronavirus disease 2019-related Case-Fatality Rates across Seventeen Nations

Ashley Wendell Kranjac [a] and Dinko Kranjac [b]

[a]Department of Sociology, Chapman University, Orange, CA, USA; [b]Department of Psychology, University of La Verne, La Verne, CA, USA

ABSTRACT
As of 1 November 2020, estimated case-fatality rates associated with coronavirus disease 2019 are not uniformly patterned across the world and differ substantially in magnitude. Given the global spatial heterogeneity in case-fatality rates, we applied the Blinder-Oaxaca regression decomposition technique to identify how putative sociodemographic, structural, and environmental sources influence variation in case-fatality rates. We show that compositional and associational differences in country-level risk factors explain a substantial proportion of the coronavirus disease 2019-related case-fatality rate gap across nations. Asian countries fair better vis-à-vis case-fatality rate differences mainly due to variation in returns to sociodemographic, structural, and environmental sources among their citizens, relative to those who share similar attributes but live in Europe or North America. The variation in case-fatality rate is driven by Asian populations being better able to buffer the harmful effects of the very risk factors purported to exacerbate the risk of coronavirus disease 2019-related death. The dire circumstances in which we find ourselves demand better understanding of how preexisting conditions across countries contribute to observed disparities in case-fatality rates.

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Introduction

In January 2020, Chinese health authorities identified severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) as the causative agent for a cluster of pneumonia cases initially detected in December of 2019 in the city of Wuhan [1]. Since then, the incidence of coronavirus disease 2019 (Covid-19), the illness caused by SARS-CoV-2, has risen exponentially [2]. By mid-March 2020, Covid-19 spread across the world, albeit with substantial global spatial heterogeneity in the number of reported cases across different countries [3]. Related, the reported Covid-19-related case-fatality rates (CFR), defined as the number of deaths in persons who tested positive for SARS-CoV-2 divided by the number of SARS-CoV-2 cases, differ substantially in magnitude, from an estimated 0.27% in Singapore, 2.16% in South Korea, and 2.86% in Germany to 10.46% in Spain and 13.95% in Belgium [4].

Also relevant are the sociodemographic, structural, and environmental risk factors associated with Covid-19-related CFR. For example, Covid-19 is substantially more lethal in older persons, and CFR rises sharply with age, from an estimated 0.02%–0.32% in the 30–39 age group and 1.12%–10.89% in the 60–69 age group, to 5.68%–26.69% in the 70–79 age group and 13.4%–38.44% in those aged 80 years or older [5–8]. In addition to the devastating impact of Covid-19 on the elderly, individuals with obesity are greatly affected by SARS-CoV-2 in terms of the risk of hospitalization [9]. One of the more readily predictable risk factors for infectious disease transmission is higher population density, which may, in part, account for geographic differences in numbers of COVID-19 cases [10]. With regard to the environmental risk factors, long-term exposure to higher concentrations of ambient air pollutants such as particulate matter ($PM_{2.5}$) is a potent driver of the observed upward trend in Covid-19-related CFR [11]. To minimize viral transmission and keep mortality rates exacerbated by these risk factors as low as possible, governments around the world instituted a number of mitigation efforts, including physical distancing, school and workplace closures, cancelation of large-scale public gatherings, and stay-at-home orders [12,13].

The above-cited reports emphasize the association between Covid-19-related CFR and sociodemographic and environmental risk factors. However, researchers have yet to completely account for the estimated CFR disparities across countries. To this end, and given the irregular spatial patterning in CFR, we examine putative sociodemographic, structural, and environmental drivers of higher CFR estimates across 17 nations affected by the Covid-19 pandemic [3]. We acknowledge that CFR will likely shift in response to improved testing and reporting practices, and thus, over time, enable the emergence of more accurate and useful

CONTACT Ashley Wendell Kranjac kranjac@chapman.edu Department of Sociology, Chapman University, Orange, CA, USA
Supplemental data for this article can be accessed here.

data [4]. Still, we use the latest data available to us as this devastating pandemic continues to unfold [3].

Methods

In our analyses, we used cumulative counts of SARS-CoV-2-diagnosed infections and deaths attributable to Covid-19 reported by the European Center for Disease Prevention and Control (ECDC) during 13 January 2020–1 November 2020 for the following nations (in alphabetical order, and grouped by geographic regions): Hong Kong, Japan, South Korea, and Taiwan (Eastern Asia); Malaysia, Singapore, and Thailand (South-eastern Asia); United Kingdom (Northern Europe); Italy and Spain (Southern Europe); Belgium, France, Germany, Netherlands, and Switzerland (Western Europe); and Canada and the United States (North America) [3]. We included data starting with 13 January 2020 when Thailand recorded its first Covid-19 case, which is the earliest recorded case across all of the nations under study [3]. In terms of total cases and fatalities attributable to Covid-19, the above listed European and North American countries find themselves atop the list of countries most heavily impacted by the pandemic [3]. Conversely, the above mentioned Eastern and South-eastern Asian countries are some of the least affected countries, both in terms of the total number of diagnosed infections and deaths attributable to Covid-19[3].

We captured SARS-CoV-2-related fatalities using Covid-19 CFR, defined as the ratio of Covid-19-related deaths divided by the number of Covid-19 diagnosed cases [5,14]. We included multiple factors that likely associate with higher CFR, including median age [15-], percent of the population that is female [16], percent classified as obese [17], percent with asthma [18], smoking prevalence [19], percent with high blood pressure [20], percent with diabetes [18], $PM_{2.5}$ mean annual exposure [21], number of hospital beds per 1000 individuals [22], and population density [23]. Many of these factors are highly correlated, and thus we represented them in a more parsimonious way by taking the first dimension of a principal components factor analysis that weighted each variable based upon its factor loading. All loadings exceed 0.40, eigenvalue is >1, and internal consistency, as measured by Cronbach's α, is 0.533 (Table 1). We defined this newly constructed measure as country-level 'risk.' Time is a continuous measure defined in number of days since the earliest recorded case across all nations under study. Our entire study period is 294 days: 13 January 2020–1 November 2020. Exploratory analyses indicated that CFR is most appropriately captured by a quadratic function due to the non-linear relationship between CFR and time. As such, we only present estimates with the quadratic time term included. We also included a physical distancing measure denoted as a time-ordered series of dichotomous variables based on school closure dates [24] to account for variation in the enactment of behavioral mitigation strategies across countries. This physical distancing measure equals 1 if schools were closed on a given date and 0 if otherwise.

Table 1. Results from the First Loading of a Principal Components Factor Analysis (Data are from 2016 to 2017 Our World in Data and the World Bank).

Variable	Factor
Risk	
Mean PM[2,5]	0.55
Obesity Prevalence	0.43
Daily Smoking Prevalence	−0.70
Asthma Prevalence	−0.40
Percent High Blood Pressure	0.54
Diabetes Prevalence	0.79
Percent of Total Population Female	0.42
Median Age	−0.56
Hospital Beds per 1k	−0.44
Eigenvalue	2.73

We used the Blinder-Oaxaca regression decomposition technique to identify the sources of Covid-19-related differences in CFR across countries [25–29]. Our modeling approach permits decomposition between two groups only [25–29]. Accordingly, the populations under study were grouped into 'high-mortality-low-risk' (i.e., relatively more impacted; the United States, United Kingdom, Italy, France, Spain, Belgium, Germany, Canada, the Netherlands, Switzerland) and 'low-mortality-high-risk' (i.e., relatively less impacted; Taiwan, Hong Kong, Singapore, Malaysia, Thailand, South Korea, Japan), based upon the cumulative number of reported Covid-19-related deaths as of 1 November 2020. More specifically, high-mortality-low-risk countries fall within the 4^{th} quartile, and low-mortality-high-risk countries between the 1^{st} and 3^{rd} quartiles, based upon the total number of fatalities within a country across all the countries in the world, up to 1 November 2020[3]. As an example, Switzerland (high-mortality-low-risk) and Taiwan (low-mortality-high-risk) recorded a total of 2,097 and 7 deaths by 1 November 2020, respectively, despite the fact that Switzerland has a population about one-third the size of Taiwan [3]. Moreover, United Kingdom (high-mortality-low-risk) and Thailand (low-mortality-high-risk) recorded a total of 46,555 and 59 deaths by 1 November 2020, respectively, despite having similar population sizes [3]. We defined the 'high-mortality-low-risk' designation as the reference group to ensure our estimates from the original Blinder-Oaxaca method are unbiased [27]. To explain the difference in CFR between the two groups (i.e., high-mortality-low-risk *versus* low-mortality-high-risk), we used a stepwise process, and stratification was necessary in each step [25–29].

The first step in partitioning the CFR gap is to estimate the sample means for high-mortality-low-risk and low-mortality-high-risk group covariates to identify differences between country groupings. In the second step, we estimated separate regression equations by country grouping (i.e., high-mortality-low-risk and low-mortality-high-risk) and then used the estimated coefficients and intercept from each of these regression equations, as well as the sample means for the covariates estimated in step one, to compute two counterfactuals. The first counterfactual quantifies how CFR would have differed *if* compositional differences by country consisted of the compositional makeup of high-mortality-low-risk countries and *if* the regression coefficients did not differ (i.e., the regression coefficients for high-mortality-low-risk and low-mortality-high-risk countries are the same). This addresses whether differences in CFR exist between country groupings because, for example, asthma is more prevalent among citizens in European and North American (high-mortality-low-risk) countries, compared with asthma prevalence among citizens in Asian (low-mortality-high-risk) countries. Thus, the value of the first counterfactual represents the contribution of differences in the mean levels of the covariates between the country groupings (i.e., differences in compositional makeup of high-mortality-low-risk and low-mortality-high-risk countries).

The second counterfactual quantifies how CFR would have differed *if* the regression coefficients and intercept differed as they did between the two country groupings and *if* the compositional makeup of countries *did not* differ (i.e., the means between high-mortality-low-risk and low-mortality-high-risk countries are the same). This addresses whether CFR differences exist between country groupings because citizens in high-mortality-low-risk countries, for example, are less able to reduce personal health risks from exposure to air pollutants due to a lack of resources (e.g., inability to clean indoor air with air filters), relative to those citizens in low-mortality-high-risk countries. The value of the second counterfactual represents the contribution of differences in the regression coefficients and intercepts between high-mortality-low-risk and low-mortality-high-risk countries (i.e., differences in associations or magnitude of determinants). The decomposition is estimated from the 'perspective' of high-mortality-low-risk countries.

Results

Table 2 displays means and standard deviations for independent and dependent variables by country grouping [i.e., high-mortality-low-risk (Belgium, Canada, France, Germany, Italy, the Netherlands, Spain, Switzerland, United Kingdom, the United States) and low-mortality-high-risk (Hong Kong, Japan, Malaysia, Singapore, South Korea, Taiwan, Thailand)]. The difference in CFR may be a consequence of differences in the population composition of high-mortality-low-risk and low-mortality-high-risk countries. CFR varies significantly by country-grouping designation, with high-mortality-low-risk country group estimation higher than low-mortality-high-risk. Examples of this divergence are shown in Supplemental Figures 1 and 2 where we plot the change in CFR over time during the length of our study period separately for high-mortality-low-risk and low-mortality-high-risk countries.

Table 2. Means and Standard Deviations for Independent and Dependent Variables by Country Type, January 13–1 November 2020.

	High-Mortality-Low-Risk		Low-Mortality-High-Risk		Diff.
Dependent Variable	Mean	SD	Mean	SD	
Case Fatality Rate (CFR)	7.84	5.13	1.54	2.03	***
Cumulative Deaths	25,156.23	41,150.37	202.62	364.54	***
Cumulative Cases	499,456.10	1,337,081.00	14,976.52	21,070.23	***
Independent Variables					
Time	165.34	74.19	159.52	79.94	***
Time[2]	32,838.70	25,032.15	31,832.29	25,791.12	***
Daily Smoking Prevalence	25.40	5.06	19.04	4.07	***
Asthma Prevalence	5.85	1.46	4.73	0.25	***
Percent High Blood Pressure	17.78	3.00	19.33	5.57	***
Diabetes Prevalence	6.28	2.02	9.61	3.58	***
Percent of Total Population Female	50.67	0.29	50.65	1.50	
Mean PM[2,5]	12.05	2.75	23.12	7.17	***
Obesity Prevalence	24.34	5.07	13.07	13.46	***
Median Age	43.07	2.77	41.47	5.43	***
Hospital Beds per 1k	4.50	1.83	6.76	4.92	***
PCFA 'Risk' Score	−0.22	0.39	0.54	1.17	***
Population Density	204.68	146.41	2448.61	3247.81	***
Physical Distancing Date Range	3.20. – 4.01.2020		1.25. – 3.02.2020		***

Source: Data are from the European Center for Disease Control and Prevention, World Bank, Our World in Data, UNESCO Global Education Coalition, and the World Health Organization
Note: Asterisks indicate significant difference evaluated using two-tailed independent means t-test by country type
Note: PCFA = Principal Components Factor Analysis
$*p < .05$, $**p < .01$, $***p < .001$

Nearly all population-level risk factors purported to increase Covid-19-related CFR vary significantly across country groupings, aside from the percentage of females in the population. More specifically, in low-mortality-high-risk countries a greater proportion of the population suffers with hypertension (high-mortality-low-risk: 17.78% *vs*. low-mortality-high-risk: 19.33%) and diabetes (high-mortality-low-risk: 6.28% *vs*. low-mortality-high-risk : 9.61%). Population density is higher in low-mortality-high-risk (2448.61 per square mile) countries, compared to high-mortality-low-risk (204.68 per square mile) countries. Median age is 43.07 in high-mortality-low-risk countries and 41.47 years of age in low-mortality-high-risk countries. High-mortality-low-risk, relative to low-mortality-high-risk, countries have a lower overall estimated risk score (-0.22 *vs*. 0.54, respectively). It is worth noting that despite variation in the means across the very risk factors purported to drive case-fatality rates, CFR averages remain highest in country groupings that score the lowest across many of these risk factors (see the upper and lower portions of Table 2). Appendix 1 presents a breakdown of the means and standard deviations for these risk factors by country. Additionally, as shown, the date of enactment of physical distancing measures (i.e., date of school closures) varies significantly across countries, from 25 January 2020 in Hong Kong (low-mortality-high-risk) and 2 March 2020 in Japan (low-mortality-high-risk) to 20 March 2020 in United Kingdom (high-mortality-low-risk) and 1 April 2020 in Canada (high-mortality-low-risk) [24].

CFR may also vary by country grouping because the associations between population-level risk factors and CFR differ. Table 3 displays the estimated coefficients from Ordinary Least Squares (OLS) models regressing CFR on risk while accounting for variation in population density, time, and timing of the enactment of physical distancing measures (i.e., school closure dates).

The initial estimated CFR is significantly different between country groupings and is greater in magnitude in low-mortality-high-risk countries (2.15, $p < 0.001$), relative to high-mortality-low-risk countries (-7.64, $p < 0.001$). With the passage of time, CFR increases in high-mortality-low-risk and low-mortality-high-risk country groupings, as evidenced by the positive values for the linear components of the time slope (0.21 and 0.01, $p < 0.001$), and the negative values for the quadratic components of the time slope (-0.00 and -0.00, $p < 0.001$). Both country groupings indicate non-linearity in the time trend. Regression estimates indicate further that the early enactment of physical distancing measures led to a 0.23-point reduction in CFR among high-mortality-low-risk countries ($p < 0.001$), while resulting in a lower magnitude decline of CFR in low-mortality-high-risk countries (-0.20, $p < 0.001$). The associations between risk and CFR differ significantly between country groupings. As risk increases, CFR significantly increases, on average, by 0.17 points in low-mortality-high-risk countries ($p < 0.01$), whereas high-mortality-low-risk countries see a significant decrease of -2.61 ($p < 0.001$).

The Blinder-Oaxaca results are displayed in Table 4. We present the unique contributions of compositional and associational effects on the total CFR difference between country groupings attributable to the

Table 3. OLS Regression Estimates For Covid-19-Related Case Fatality Rates by Country Type, January 13–1 November 2020; N = 4,098.

	High-Mortality-Low Risk		Low Mortality-High-Risk		Diff.
	Coeff.	St. Err.	Coeff.	St. Err.	
Intercept	−7.64***	0.39	2.15***	0.21	***
Independent Variables					
Time	0.21***	0.01	0.01***	0.00	***
$Time^{[2]}$	−0.00***	0.00	−0.00***	0.00	***
Population Density	0.01***	0.00	−0.00***	0.00	***
Physical Distancing	−0.23***	0.02	−0.20***	0.02	***
Risk	−2.61	0.24	0.17**	0.05	***

Source: Data are from the European Center for Disease Control and Prevention, World Bank, Our World in Data, UNESCO Global Education Coalition, and the World Health Organization
Note: Significance between country types is evaluated using simple linear or logistic regression with High-Mortality-Low-Risk as the reference
**p < .05, **p < .01, ***p < .001*

Table 4. Regression Decomposition of Covid-19-Related Case Fatality Rates by Country Type, January 13–1 November 2020; N = 4,098.

	Coeff.	St. Err.
Differential		
High-Mortality-Low-Risk Group Prediction	7.84***	0.10
Low-Mortality-High-Risk Group Prediction	1.54***	0.05
Difference	6.30***	0.12
Decomposition		
Endowments	0.54***	0.05
Coefficients	10.65***	1.63
Interaction	−4.90***	1.63

Source: Data are from the European Center for Disease Control and Prevention, World Bank, Our World in Data, UNESCO Global Education Coalition, and the World Health Organization
**p < .05, **p < .01, ***p < .001*

population-level sociodemographic, structural, and environmental factors. Again, in our model, we conceptualized these factors as 'risk.' The interaction term reflects the fact that differences in endowments and differences in the associations between covariates and CFR occur together [28]. Some studies incorporate this interaction term into either the associational or compositional portion of the decomposition [29], but we retain the interaction term because it provides a more conservative test of the relative importance of differences in country compositions and associations. Moreover, prior theory on CFR does not generate specific hypotheses regarding the interaction between differences in compositions and associations. As such, we refrain from interpreting the interaction term.

The CFR differs by 6.30% between the two country groupings (7.84 in high-mortality-low-risk and 1.54 in low-mortality-high-risk; $p < 0.001$). Population compositional differences explain a small but significant proportion of the CFR variation between country groupings (0.54%, $p < 0.001$) indicating that compositional differences, designated here as 'risk,' contribute to CFR disparities between high-mortality-low-risk and low-mortality-high-risk countries. As an example, because higher proportions of people suffer with obesity in the United States and United Kingdom (both high-mortality-low-risk), relative to Japan and Singapore (both low-mortality-high-risk) (i.e., differences in sample means shown in Table 2), there is a higher percentage of the population at risk for this factor purported to exacerbate Covid-19-related CFR, and this difference contributes to the variation in CFR between country groupings. Still, it is beyond the scope of our analysis to disentangle which of these factors drive this variation given our use of a factor analysis to more parsimoniously represent these highly collinear measures of risk.

The principal factor responsible for the difference in CFR between high-mortality-low-risk and low-mortality-high-risk countries is the differences in the associations between country groupings and the included population-level risk factors (10.65%, $p < 0.001$). Indeed, the difference attributable to factors conceptualized as 'risk' in our models (i.e., median age, percent of the population that is female, percent classified as obese, percent with asthma, smoking prevalence, percent with high blood pressure, percent with diabetes, $PM_{2.5}$ mean annual exposure, and number of hospital beds per 1000 individuals), while holding population density, time, and physical distancing enactment differences (i.e., school closure dates) constant, is significantly linked to CFR variation. In fact, as shown in Table 4, net of other factors, some of which counteract the positive effect of difference in CFR, variation in the coefficients for the sociodemographic, structural, and environmental characteristics, defined here as 'risk,' explains a greater proportion of country-level disparities between high-mortality-low-risk and low-mortality-high-risk countries than compositional differences between country groupings. This variation in CFR is linked comparatively more to differences in the estimated coefficients for risk in our models. In short, our decomposition indicates that despite greater 'risk' among citizens of low-mortality-high-risk nations, these differences are not driving CFR disparities across country groupings. Instead, preexisting inequities in high-mortality-low-risk countries seem to create an environment wherein an individual diagnosed with Covid-19 may be less able to buffer the harmful effects of viral infection, leading to higher CFR in these nations. For illustrative purposes, in Supplemental Figure 3, we graphed the mean CFR change over time during the length of our study period for high-mortality-low-risk and low-mortality-high-risk country groupings. Moving from left to right in Supplemental Figure 3, the average CFR gap widens over time between high-mortality-low-risk and low-mortality-high-risk country groupings. More specifically, mean CFR increases from a low of 0.20% (24 February 2020) to a high of 11.40% (25 May 2020) in high-mortality-low-risk countries, and from 1.20% to 1.80% in low-mortality-high-risk countries, during that same time period.

Discussion

Overall, our results for January 13–1 November 2020, confirm that the Covid-19-related case-fatality rate (CFR) is higher across European and North American (high-mortality-low-risk) nations than that observed in the Asian (low-mortality-high-risk) populations under study, as was shown previously **[**4,5,14**]**. We add to this literature by providing evidence that compositional and associational differences in country-level social (median age, obesity prevalence, percent with diabetes, percent with hypertension, asthma prevalence, population density), structural (number of hospital beds per 1000 individuals), and environmental (ambient air pollution) factors, conceptualized as 'risk,' explain a substantial proportion of the Covid-19-related CFR gap across country groupings (i.e., high-mortality-low-risk *vs.* low-mortality-high-risk). Importantly, despite that compositional differences explain only a small share of the overall CFR gap between high-mortality-low-risk and low-mortality-high-risk countries, variation in CFR averages remain highest in countries that score the lowest across these risk factors.

Relatedly, we show that Asian countries (low-mortality-high-risk) fair better, vis-à-vis Covid-19-related CFR, even with the higher observed risk score, relative to high-mortality-low-risk countries. CFR is lower in Asian, relative to European and North American, nations partially because the magnitude of the association attributable to country-level characteristics is higher in Europe and North America. This variation may be driven by low-mortality-high-risk populations being better able to buffer the harmful effects of sociodemographic, structural, and environmental factors that exacerbate the risk of Covid-19-related death, leading to lower overall CFR, relative to European or North American (high-mortality-low-risk) nations. The difference in returns to sociodemographic, structural, and environmental characteristics among citizens in Asian nations, relative to those populations who share similar circumstances but live in Europe or North America, contributes to the observed disparities in CFR. This latter finding clearly underscores the importance of relating social determinants of health to 'risk,' but it is beyond the scope of our analysis to parse out which of the factors matter most. Still, we offer some potential explanations.

Lessons learned from Singapore, for example, show that early intervention and widespread availability of diagnostic tests is paramount [30]. The earlier the identification and isolation of persons infected with SARS-CoV-2, the better the control of transmission [30]. Early detection is likely to lead to less severe clinical outcomes, and possibly decrease the risk of death from Covid-19 [30]. Moreover, widespread surveillance testing enables faster contact tracing, which is a mainstay of infectious disease control [31]. It is also worth noting that since the outbreak of SARS-CoV-2 the uncertainty about the efficacy of surgical masks to reduce virus transmission among the general public has resulted in inconsistent recommendations by health authorities in different countries about the widespread use of face masks [32]. Consequently, the use of face masks in public was, in part, influenced by social norms and values already embedded in the cultural background of nations [33]. In many Asian countries, mask-wearing is destigmatized and is commonplace since 2003 as SARS spread around China and neighboring countries [33]. The latter point is significant because face masks may result in a large reduction in risk of infection [34]. Related, governments of Hong Kong and Singapore built a more robust public health system following the outbreak of H5N1 avian influenza in 1997 and H1N1 influenza in 2009, which, in part, enabled a more efficient response to the current Covid-19 pandemic [33].

To the best of our knowledge, this is the first study that employed Blinder-Oaxaca regression decomposition technique [25–29] to identify the sources of Covid-19-related differences in CFR across countries. This study, however, is not without limitations. The published reports indicate that, especially during the early phase of Covid-19 outbreak, limited diagnostic testing and hospital bed capacity, and testing or reporting delays may influence the number of daily reported cases across countries [35]. However, for countries in our sample with data available, the Covid-19 incidence curve parallels the growth rate of deaths and hospitalizations [36–40], two measures that may be a less biased metric of a Covid-19 outbreak [35], giving us confidence in the estimates presented here. Related, we were unable to control for the amount of testing across countries because some governments report the number of Covid-19 tests performed (e.g., Belgium, France, Germany, Hong Kong, Spain, Switzerland, Thailand, United Kingdom, the United States), while others report the number of people tested (e.g., Canada, the Netherlands, Taiwan) [41]. For example, as of 2 November 2020, in Singapore, a total of 1.1 million unique persons were swabbed, and a total of 3.8 million swabs were tested [42]. Theoretically, then, since the same person may be tested more than once, the number of tests performed may be higher. Additionally, our sample is restricted to 17 nations and data are drawn from six geographic regions, thus reducing the generalizability of our findings to a particular portion of people in Eastern Asia, South-eastern Asia, Northern Europe, Southern Europe, Western Europe, and North America through 1 November 2020. Also, given that dates of the first recorded case differ across countries [3] [e.g., Thailand (low-mortality-high-risk) on 13 January 2020, Japan (low-mortality-high-risk) on 16 January 2020, the United States of America (high-mortality-low-risk) on 21 January 2020, and the Netherlands (high-mortality-low-risk) on 27 February 2020], and we include data starting with 13 January 2020, when Thailand recorded its first Covid-19 case (i.e., the earliest recorded case across all of the nations under study) [3], our estimates may be attenuated. Finally, although government officials across the world enacted a number of personal protective behaviors such as social distancing, workplace closures, cancelation of large-scale public gatherings, and stay-at-home orders [13,30,31], we used school closure dates [24] to account for variation in the enactment of behavioral mitigation efforts across countries. We opted to use this measure given that governments worldwide introduced school closures early on in their initial response to the SARS-CoV-2 outbreak [43].

Despite these limitations, we are the first to show that citizens of the Asian nations under study are exposed to higher levels of social, structural, and environmental risk, relative to European and North American countries included in our analyses. Yet, these differences in risk are not driving CFR disparities across countries. Instead, preexisting sociodemographic, structural, and environmental inequities in European and North American nations seem to create an environment wherein an individual diagnosed with Covid-19 may be less able to buffer the harmful effects of viral infection, leading to higher rates of Covid-19-related mortality.

Disclosure statement

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ORCID

Ashley Wendell Kranjac http://orcid.org/0000-0002-8187-7730
Dinko Kranjac http://orcid.org/0000-0001-5002-6151

Ethics approval

We use data from a publicly accessible repository.

References

[1] Li Q, Guan X, Wu P, et al. Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. NEJM. 2020;382:1199–1207.
[2] Cucinotta D, Vanelli M. WHO declares COVID-19 a pandemic. Acta Biomed. 2020;91:157–160.
[3] European Centre for Disease Prevention and Control. The geographic distribution of COVID-19 cases worldwide. Accessed November 1, 2020. https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide
[4] Hui PG, Mahari WI, Ahad NI, et al. 2020. Risk factors affecting Covid-19 case fatality rate: A quantitative analysis of top 50 affected countries. medRxiv. DOI:10.1101/2020.05.20.20108449
[5] Dudel C, Riffe T, Acosta E, et al. 2020. Monitoring trends and differences in Covid-19 case fatality rates using decomposition methods: contributions of age structure and age-specific fatality. medRxiv. DOI:10.1101/2020.03.31.20048397
[6] Onder G, Rezza G, Brusaferro S. 2020. Case-fatality rate and characteristics of patients dying in relation to Covid-19 in Italy. JAMA. DOI:10.1001/jama.2020.4683
[7] Verity R, Okell LC, Dorigatti I, et al. 2020. Estimates of the severity of coronavirus disease 2019: a model-based analysis. Lancet Infect Dis. DOI:10.1016/S1473-3099(20)30243-7.
[8] Green MS, Peer V, Schwartz N, et al. 2020. The confounded crude case-fatality rates for Covid-19 hide more than they reveal—a comparison of age-specific and age-adjusted CFRs between seven countries. PLoS One. DOI:10.1371/journal.pone.0241031
[9] Petrilli CM, Jones SA, Yang J, et al. 2020. Factors associated with hospitalization and critical illness among 4,103 patients with Covid-19 disease in New York City. medRxiv. DOI:10.1101/2020.04.08.20057794
[10] Li R, Pei S, Chen B, et al. 2020. Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV-2). Science. DOI:10.1126/science.abb3221.
[11] Wu X, Nethery RC, Sabath BM, et al. 2020. Exposure to air pollution and Covid-19 mortality in the United States. medRxiv. DOI:10.1101/2020.04.05.20054502
[12] Chin T, Kahn R, Li R, et al. 2020. U.S. county-level characteristics to inform equitable Covid-19 response. medRxiv. DOI:10.1101/2020.04.08.20058248.
[13] Koo JR, Cook AR, Park M, et al. 2020. Interventions to mitigate early spread of SARS-CoV-2 in Singapore: a modelling study. Lancet Infect Dis. DOI:10.1016/S1473-3099(20)30162-6.
[14] Spychalski P, Błażyńska-Spychalska A, Kobiela J. 2020. Estimating case fatality rates of COVID-19. Lancet. DOI:10.1016/S1473-3099(20)30246-2
[15] Ritchie H, Roser M "Age structure". Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/age-structure
[16] Ritchie H, Roser M "Gender ratio". Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/gender-ratio
[17] Ritchie H, Roser M "Obesity". Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/obesity
[18] Ritchie H, Roser M Burden of disease. Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/burden-of-disease
[19] Ritchie H, Roser M "Smoking". Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/smoking.
[20] World Health Organization. Mean systolic blood pressure (age-standardized estimate). Accessed November 1, 2020. https://www.who.int/data/gho/data/indicators/indicator-details/GHO/mean-systolic-blood-pressure-(age-standardized-estimate)
[21] The World Bank. $pm^{2.5}$ air pollution, mean annual exposure. Accessed November 1, 2020. https://data.worldbank.org/indicator/en.atm.pm25.mc.m3
[22] The World Bank. Hospital beds per 1,000 people. Accessed November 1, 2020. https://data.worldbank.org/indicator/sh.med.beds.zs
[23] Ritchie H, Roser M "Population density". Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/population-density
[24] UNESCO. Global Education Coalition. Covid-19 Impact on Education. Accessed November 1, 2020. https://en.unesco.org/covid19/educationresponse
[25] Blinder AS. Wage discrimination: educed form and structural estimates. J Hum Resour. 1973;8:436–455.
[26] Oaxaca R. Male-female wage differentials in urban labor markets. Int Econ Rev. 1973;14:693–709.
[27] Kim CH. Detailed wage decompositions: revisiting the identification problem. Soc Method. 2013;43(1):346–363.
[28] Jann B. The Blinder-Oaxaca decomposition for linear regression models. Stata J. 2008;8(4):453–479.
[29] Jones F, Kelley J. Decomposing differences between groups: a cautionary note on measuring discrimination. Social Methods Res. 1984;12(3):323–343.
[30] Ng Y, Li Z, Chua YX, et al. Evaluation of the effectiveness of surveillance and containment measures for the first 100 patients with Covid-19 in Singapore—January 2–February 29, 2020. MMWR Morb Mortal Wkly Rep. 2020;69:307–311.
[31] Wang CJ, Ng CY, Brook RH. Response to Covid-19 in Taiwan. Big data analytics, new technology, and proactive testing. JAMA. 2020;323:1341–1342.
[32] Leung NHL, Chu DKW, Shiu EYC, et al. 2020. Respiratory virus shedding in exhaled breath and efficacy of face masks. Nat Med. DOI:10.1038/s41591-020-0843-2.
[33] Legido-Quigley H, Asgari N, Teo YY, et al. Are high-performing health systems resilient against the Covid-19 epidemic? Lancet. 2020;395:848–850.
[34] Chu DK, Akl EA, Duda S, et al. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and Covid-19:

a systematic review and meta-analysis. Lancet. 2020;395:1973–1987.
[35] Omori R, Mizumoto K, Chowell G. Changes in testing rates could mask the Covid-19 growth rate. Int J Infect Dis. 2020;94:116–118.
[36] Gov. UK. Coronavirus (COVID-19) in the UK. Accessed November 1, 2020. https://coronavirus.data.gov.uk/
[37] European Centre for Disease Prevention and Control. Data on hospital and ICU admission rates and current occupancy for Covid-19. Accessed November 1, 2020. https://www.ecdc.europa.eu/en/publications-data/download-data-hospital-and-icu-admission-rates-and-current-occupancy-covid-19
[38] Ritchie H, Ortiz-Ospina E, Beltekian D, et al. Daily new confirmed Covid-19 deaths". Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/coronavirus-data
[39] Ritchie H, Ortiz-Ospina E, Beltekian D, et al. "Coronavirus (Covid-19) Hospitalizations". Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/covid-hospitalizations
[40] Ritchie H, Ortiz-Ospina E, Beltekian D, et al. Daily new confirmed Covid-19 deaths". Our World in Data. Accessed November 1, 2020. https://ourworldindata.org/covid-cases#what-is-the-daily-number-of-confirmed-cases
[41] Hasell J, Mathieu E, Beltekian D, et al. "A cross-country database of Covid-19 testing". Our World in Data. Accessed November 3, 2020. https://ourworldindata.org/coronavirus-testing
[42] Singapore Ministry of Health. Updates on Covid-19 Local Situation. Accessed November 3, 2020. https://moh.gov.sg/covid-19
[43] Klimek-Tulwin M, Tulwin T. Early school closures can reduce the first-wave of the Covid-19 pandemic development. J Public Health. 2020. DOI:10.1007/s10389-020-01391-z