



# Disparities in COVID-19 health outcomes among different sub-immigrant groups in the US - a study based on the spatial Durbin model

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# Abstract

Immigrants may be more vulnerable to coronavirus disease 2019 (COVID-19) than other sub-population groups due to their relatively low socioeconomic status. However, no quantitative studies have examined the relationships between immigrants and COVID-19 health outcomes (confirmed cases and related deaths). We first examined the relationship between total immigrants and COVID-19 health outcomes with spatial Durbin models after controlling for demographic, biophysical and socioeconomic variables. We then repeated the same analysis within multiple subimmigrant groups divided by those with original nativity to examine the differential associations with health outcomes. The result showed that the proportion of all immigrants is negatively associated with the number of confirmed cases and related deaths. At the continent and sub-continent level, we consistently found negative relationships between the number of confirmed cases and the proportion of all sub-immigrant groups. However, we observed mixed associations between the proportion of sub-immigrant groups and the number of deaths. Those counties having a higher prevalence of immigrants from Africa [Eastern Africa: -18.6, 95% confidence interval (CI): -38.3~-2.9; Northern Africa: -146.5, 95% CI: -285.5~-20.1; Middle Africa: -622.6, 95% CI: -801.4~ 464.5] and the Americas (Northern America: -90.5, 95% CI: -

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See online Appendix for supplementary materials.

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This article is distributed under the terms of the Creative Commons Attribution Noncommercial License (CC BY-NC 4.0) which permits any noncommercial use, distribution, and reproduction in any medium, provided the original author(s) and source are credited. 106.1~73.8; Latin America: -6.8, 95% CI: -8.1~5.2) mostly had a lower number of deaths, whereas those counties having a higher prevalence of immigrants from Asia (Eastern Asia: 21.0, 95% CI: 7.7~36.2; Western Asia: 42.5, 95% CI: 16.9~68.8; South-Central Asia: 26.6, 95% CI: 15.5~36.9) showed a higher number of deaths. Our results partially support that some immigrants, especially those from Asia, are more vulnerable to COVID-19 than other sub-population groups.

# Introduction

In December 2019, an outbreak of pneumonia caused by a novel coronavirus, later designated as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was reported in Wuhan, China. The virus has rapidly spread across China and other countries, resulting in more than 398.2 million confirmed cases and 5.8 million deaths as of February 8, 2022 (Johns Hopkins Coronavirus Resource Center, 2021). Common symptoms of the virus are fever, cough, fatigue, and muscle aches (Huang *et al.*, 2020). The virus spreads through direct contact or droplets generated by breathing, sneezing and coughing (Ong *et al.*, 2020).

Previous studies reported that environmental factors may influence the transmission of coronavirus (Van Doremalen et al., 2013). For coronavirus disease 2019 (COVID-19), scholars found a negative relationship between confirmed cases/mortality and temperature (Prata et al., 2020; Qi et al., 2020). While this relationship has the most robust support, other scholars also report both positive relationships (Xie and Zhu, 2020) and no association (Jamil et al., 2020). The different relationships might be from multiple regional factors such as health infrastructure, socioeconomic background and the availability of adequate health supplies (Bhadra et al., 2021; Hamidi et al., 2020). Other environmental factors such as humidity (Qi et al., 2020) and diurnal temperature variation also have a significant association with COVID-19 health outcomes (Ma et al., 2020). These factors can impact the degree of virus transmission by changing host behaviour (e.g., time spent indoors, protective behaviour, risk perception), host defence mechanisms (e.g., vitamin D deficiency, impairment of mucociliary clearance with inhalation of cold, dry air) and virus infectivity and stability (Pica and Bouvier, 2012).

Demographic and socioeconomic factors also play an important role in spreading COVID-19 disease. Many papers showed that age, sex, and race/ethnicity could directly or indirectly impact susceptibility to virus infection (Golestaneh *et al.*, 2020; Ludvigsson, 2020; MohammadEbrahimi *et al.*, 2021). For example, Garg *et al.* (2020) found a higher hospitalization rate for males, Blacks and those over 65 years old. Low income and





poverty also tend to increase the rate of infection (Hawkins *et al.*, 2020). Multiple studies support that higher social and material deprivation elevates the risk of virus infection and death (Rutter *et al.*, 2012). These demographic and socioeconomic factors are highly associated with host behaviour and risk perception. For example, Czeisler *et al.* (2020) showed that males and young adults reported less frequent hand washing and hand sanitizing. More importantly, socioeconomically vulnerable people tend to have no or limited access to medical services (Tolbert *et al.*, 2020) and some of their jobs (*e.g.*, cleaning and transport workers) are more vulnerable due to more frequent interactions with people (Mutambudzi *et al.*, 2021). Their relatively poor residential environment (*e.g.*, multiunit housing, a higher number of people in a house) could also increase the risk of infection (Jones and Grigsby-Toussaint, 2020).

Relatedly, immigrants may be more vulnerable than other subpopulation groups due to their, on average, relatively low socioeconomic status. According to the US Census Bureau Current Population Survey (CPS) 2020 Annual Social and Economic Supplements, more non-citizens (16.4%) are below the federal poverty level than US-born citizens (10.1%) and naturalized citizens (9.1%). Non-citizens' incomes (mean: \$47,099, median: \$30,000, interquartile range: \$18,200~\$53,000) are also lower than US-born citizens' (\$56,177, \$40,000, \$20,000~70,000) and naturalized citizens' (\$63,718, \$42,500, \$25,000~75,000).Additionally, fewer noncitizens (72.4%) have health insurances than US-born citizens (93.1%) and naturalized citizens (91.2%). Similarly, the US Census Bureau American Community Survey (ACS) in 2018 shows large disparities regarding the housing environment (Langellier, 2020). Non-citizens are more likely to live in multiunit housing structures (45%) than other groups (US-born citizens: 22.1%, naturalized citizens: 34.1%). Mean bedroom occupancy is also higher in non-citizens (1.49) than US-born citizens (0.90) and naturalized citizens (0.90). The relatively worse socioeconomic status could increase the risk of coronavirus infection.

In the US, there were around 44.9 million immigrants in 2019, accounting for 13.7 percent of the total US population ('US Census Bureau ACS,' 2019). Half of these immigrants are naturalized citizens (51.6%), and the other half are noncitizens (48.4%). Most immigrants are from Latin America (50.3%) and Asia (31.4%) followed by Europe (10.4%), Africa (5.5%), Northern America (1.8%), and Oceania (0.7%). Immigrants' socioeconomic status tends to vary by original nativity (Vallejo and Keister, 2020). In general, Europe and Asia are the predominant sources of high-skilled immigrants, while Latin America, the Caribbean, and Africa are large sources of low-skilled immigrants to the US (Hanson *et al.*, 2018).

Many studies already support the idea that immigrants are more vulnerable to the COVID-19 virus than other groups (Horner *et al.*, 2021; Ross *et al.*, 2020). However, to the best of our knowledge, there is no national-level quantitative study examining the relationship between immigrants and COVID-19 health outcomes. This study is the first quantitative study investigating the disparities in COVID-19 health outcomes among different sub-immigrant groups in the US.

## Materials and methods

The present study first investigates the relationship between the proportion of all immigrants and confirmed cases/mortality with spatial models at the county level after controlling for various demographic, biophysical and socioeconomic variables. In this process, we want to make sure that all data we used in this study are county level data as opposed to individual level health and other confounding variables. We, then, repeat the same analysis within multiple sub-immigrant groups divided by original nativity to find differential associations with health outcomes. We utilize total immigrants, including both noncitizens and naturalized citizens, instead of only noncitizens in this analysis due to data availability. The research period is from January 22, 2020 to March 28, 2021. More details on the data sets and methods can be found in the following sections.

#### Weather

Monthly level parameter-elevation regressions on independent slopes model (PRISM) data provided spatially and temporally consistent 800-m resolution weather data for the continental US from 1895 to the present. The data interpolates climate data in a complex land-scape using climate-elevation regression and station weighting functions (Daly *et al.*, 2007). This study used each county's centroid to extract average, maximum, minimum, diurnal temperature range and relative humidity (RH). We calculated RH with mean temperature and mean dew point using the function dewpoint-to-humidity from the weather metrics package in R because PRISM does not provide RH. After collecting all weather data, we took their average over the research period for each county-level centroid.

## COVID-19

We downloaded daily county-level confirmed COVID-19 cases and mortality data from: i) Johns Hopkins University (https://coronavirus.jhu.edu/map.html); ii) USA Facts (https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/); and iii) The New York Times (https://www.nytimes.com/ interactive/2020/us/coronavirus-uscases.html). These websites aggregate the data from the Centers for Disease Control and Prevention (CDC) and local-level public health agencies beginning January 22, 2020. State and local agencies confirmed the county-level data. Because we could not find any significant differences among these data sets, which all show high correlations >0.998, this study only used Johns Hopkins University data. With the daily level COVID-19 health outcomes, we calculated the sum of confirmed cases and deaths at the county level. More details on statistical summaries for each data set are in Supplementary Table 1.

#### Immigrants

We used two types of immigration data retrieved from the US Census Bureau ACS 2019. At the county level, we first downloaded the total number of immigrants, which covers both non-citizens and naturalized citizens. Next, to find the differential impact based on original nativity, we downloaded data on the number of immigrants by original nativity, which also covers both non-citizens and naturalized citizens (Africa; Eastern Africa; Western Africa; Southern Africa; Northern Africa; Middle Africa; the Americas; Northern America; Latin America; Asia; Eastern Asia; Western Asia; South-Central Asia; South-Eastern Asia; Europe; Northern Europe; Western Europe; Southern Europe; Eastern Europe and Oceania). We standardized the data by dividing each immigrant measure by the total population (*i.e.* proportion of immigrants from the total population).

## Demographic and socioeconomic data

Based on previous research, we selected a total of eight demographic (population density; people under 18 years; people over 65





years; Hispanic American; Anglo American; African American; Asian American and other races) and five socioeconomic (vehicle ownership; poverty; unemployment; education less than a high school diploma and English proficiency) indicators as independent variables in the model. We retrieved all data from the US Census Bureau ACS 2019. More details on variable selection can be found in Supplementary material.

#### Statistical analysis

We used 3100 counties out of 3104 counties that do not have any missing values for independent variables. We first checked multicollinearity, which represents the linear relationship among two or more independent variables in a regression model. Multicollinearity can reduce the precision of the model by inflating and flipping the sign of regression coefficients, which weakens the statistical power of the regression model (Mansfiled and Billy, 1982). To avoid multicollinearity, we calculated the variance inflation factor (VIF), a commonly used method to detect multicollinearity. A VIF of 1 means no correlation between the independent variable and the remaining independent variables, while VIFs exceeding 5 are signs of multicollinearity (Paul, 2006). This analysis observed VIFs >5 from Anglo Americans with all statistical models; English proficiency with total immigrants and those from America and Latin America; and Asian Americans with immigrants from Asia. We, thus, deleted these variables in the corresponding models. Readers can refer to Supplementary Table 2 for more details.

We then checked for spatial autocorrelation, which explains how geographically nearby values of a particular factor tend to have similar values. We used a first-order queen contiguity matrix with row standardization to define neighbourhood weights. Spatial autocorrelation can introduce biases or errors to model regression coefficients (Anselin, 1988) and should be controlled for in the model. Spatial autocorrelation is an especially useful term to model the spread of contagious disease and the dissemination of information or ideas (Griffith, 1987). The spatial autoregressive model (SAM) and the spatial error model (SEM) are commonly used to model the spatial autocorrelation in either the dependent variable (e.g., SAM) or the error term (e.g., SEM). However, these two models have a couple of limitations. First, they only contain one spatial interaction effect. Manski (1993) proposed three types of spatial interaction effects describing how an observation at a location is associated with observations at other locations: i) endogenous interaction effects, which suggests that the observation at a region might be related to the observations of neighbouring regions; ii) exogenous interaction effects, which indicates that the observation at a region might be associated with independent explanatory variables of the observations in neighbouring regions; and iii) correlated effects, which represents that similar unobserved variables may lead to similar observations across regions. Among these three interaction effects, SAM and SEM only consider endogenous interaction effects and correlated effects, respectively. Second, both models impose prior restrictions on the magnitude of spatial spillover effects to successfully estimate models with a positive definite variancecovariance matrix (Elhorst, 2010; LeSage and Pace, 2009). These limitations could lead to biased coefficients in the model. Third, the spatial effects in the spatial lag and spatial error models do not capture both local and global spatial effects (Elhorst, 2010).

The spatial Durbin model (SDM) may outperform SAM and SEM by utilizing unbiased coefficients when the true spatial processes are either SAM or SEM and considering both local and global spatial effects with no prior restrictions on the magnitude of potential spatial interaction effects (Elhorst, 2010). This study used the SDM to examine the association between the proportion of immigrants and COVID-19 confirmed cases and deaths after adjusting for possible confounders such as environmental (*i.e.* temperature, RH and diurnal temperature range), demographic (*i.e.* population density, population over 65 and under 18 years, race/ethnicity) and socioeconomic variables (*i.e.* poverty, no vehicle, unemployment, education and English proficiency) at the county level. The SDM models have three components: endogenous interaction effects, a set of explanatory variables, and exogenous interaction effects (Equation 1).

$$Y = \rho W Y + \alpha + X \beta + W X \theta + \varepsilon \tag{1}$$

$$\varepsilon \sim N(0, \sigma^2 l_N)$$

where *Y* represents an N×1 vector of the dependent variable (*i.e.* COVID confirmed cases or deaths);  $\rho$  the spatial autoregressive coefficient; *WY* the endogenous interaction effects among the dependent variables (*i.e.* COVID confirmed cases or deaths); *X* an *N*×*K* matrix of *K* exogenous explanatory variables (*i.e.* environmental, demographic and socioeconomic variables) associated with parameter  $\beta$ ; *WY* the exogenous interaction effects among the *N*×*K* matrix of *K* independent variables (*i.e.* environmental, demographic and socioeconomic variables) associated with parameter  $\beta$ ; *wY* the exogenous interaction effects among the *N*×*K* matrix of *K* independent variables);  $\theta$  a *K*×*1* vector of the effect of *WX*; and  $\varepsilon$  the error term, which follows a normal distribution with a mean of 0 and a variance of  $\sigma^2 l_N$ .  $l_N$  is an *N*×*1* vector of those associated with the intercept parameter  $\alpha$ .

The SDM can be simplified into the SAM (when  $\theta$ =0), SEM (when  $\theta$ = –  $\rho\beta$ ) or the ordinary least squares (OLS) model (no spatial dependence) (LeSage and Pace, 2009). We used a likelihood ratio (LR) test to check if the SDM model can be restricted to one of these three models under the belief that simpler models are better (Elhorst, 2010). This tests the hypotheses H<sub>0</sub>:  $\theta$ =0 and H<sub>0</sub>:  $\theta$ + $\rho\beta$ =0. If the first hypothesis (H<sub>0</sub>:  $\theta$ =0) cannot be rejected, SAM is the best model simulating the data. SEM best describes the data if the second hypothesis (H<sub>0</sub>:  $\theta$ + $\rho\beta$ =0) cannot be rejected. If both hypotheses are rejected, then the SDM best explains the data. We found that the SDM best described the data for all models used in the study (Supplementary Table 3).

The SDM separately provides direct (i.e. within a county), indirect (i.e. to/from neighbouring counties), and total impact. In this study, we only report global average total impacts and 95% confidence intervals (CIs) because the spatial model's purpose was to control for residual spatial autocorrelation rather than to provide insight into spatial mechanisms. Through Markov chain Monte Carlo simulations (n=100), we attained empirical 95% CIs (quantiles at 2.5% and 97.5%) from the empirical distribution. We first reported the relationship between the proportion of total immigrants and COVID-19 confirmed cases and deaths with beta coefficients and 95% CIs at the county level. Then, we reported the beta coefficients and 95% CIs for multiple immigrant subgroups divided by those of original nativity to find differential associations with the confirmed cases and deaths. After these analyses, we checked spatial autocorrelation of the residuals with Moran's I, which exhibits the degree of clustering, to investigate if any assumption of the model is violated. The residuals satisfied the assumption, not exhibiting spatial autocorrelations. We used the R (V.4.0.3) statistical analysis and computing software for all calculations. SDM was employed through the lagsarlm function in the spdem package (https://cran.r-project.org/web/packages/spdep).





# Results

# **Descriptive summary**

Table 1 shows a descriptive summary of all county-level data

used in the study. It should be noted that this is a county-level summary which may show differences from the national-level. Approximately 4.77% of the total population were immigrants in 2019. Across the US, this percent ranged from 0 to 53.72%. Immigrants from the Americas (2.89%) were the highest propor-

# Table 1. A descriptive summary for the dependent and independent variables at the county level.

1 ,			•	
Origins of immigrants	Min	Mean	Max	SD
Total immigrants (%)	0	4.77	53.72	5.73
Africa (%)	0	0.21	8.75	0.49
Eastern Africa (%)	0	0.07	5.72	0.24
Western Africa (%)	0	0.00	0.53	0.02
Southern Africa (%)	0	0.01	1.32	0.06
Northern Africa (%)	0	0.00	0.95	0.03
Middle Africa (%)	0	0.00	0.84	0.03
Americas (%)	0	2.89	50.13	4.32
Northern America (%)	0	0.14	4.27	0.24
Latin America (%)	0	2.75	49.96	4.29
Asia (%)	0	1.07	34.01	1.96
Eastern Asia (%)	0	0.31	14.00	0.67
Western Asia (%)	0	0.08	3.58	0.19
South-Central Asia (%)	0	0.27	12.61	0.68
South-Eastern Asia (%)	0	0.41	32.52	1.03
Europe (%)	0	0.55	7.65	0.70
Northern Europe (%)	0	0.14	1.96	0.19
Western Europe (%)	0	0.17	3.74	0.20
Southern Europe (%)	0	0.06	5.87	0.20
Eastern Europe (%)	0	0.18	5.45	0.36
Oceania (%)	0	0.04	3.03	0.14
Demographic variables				
Population density (people per km <sup>2</sup> )	0.06	97.29	16,610.26	546.23
Under 18 years (%)	1.52	22.24	41.80	3.52
Over 65 years (%)	3.20	18.79	56.71	4.66
Hispanic American (%)	0.00	9.42	99.17	13.87
Anglo American (%)	3.60	82.93	100.00	16.88
African American (%)	0.00	9.06	87.23	14.49
Asian American (%)	0.00	1.38	42.66	2.80
Other races (%)	0.00	4.18	93.46	8.65
Socioeconomic variables				
No vehicle (%)	0.00	6.28	87.99	4.46
Poverty (%)	2.43	15.11	55.45	6.33
Unemployment (%)	0.00	5.15	27.03	2.64
Education less than a high school diploma (%)	1.12	13.05	73.56	6.26
English proficiency (not well and not at all) (%)	0.00	1.69	34.44	2.80
Biophysical variables				
Daily mean temperature (°C)	-0.01	11.25	24.81	4.78
Daily relative humidity (%)	21.94	67.43	84.59	9.86
Daily diurnal temperature variation (°C)	6.13	11.89	20.19	1.91
COVID-19				
	0	0990 40	97 101 50	2006.00
Daily confirmed cases (per 100,000)	0	9339.46	37,191.52	3086.00
Daily death (per 100,000)	0	185.65	792.86	110.29



tion of immigrants, followed by Asia (1.07%), Europe (0.55%), Africa (0.21%) and Oceania (0.04%). Immigrants from Latin America (mean number of 7,075 per county) accounted for more than 50% of the total mean number of county immigrants (13,982), while those from Middle Africa (mean number of 8 per county) accounted for only 0.06% (Supplementary Table 4).

Demographic variables covering both immigrants and nonimmigrants showed that the mean population density is approximately 97.29 people/km<sup>2</sup> (range: 0.06~16,610.26). On average, those under 18 years of age and over 65 years accounted for 22.24% (1.52~41.80) and 18.79% (3.20~56.71) of the total population. About 9.42% of the US population identified as Hispanic with high geographic variability ranging from 0.00 to 99.17%. Anglo Americans (mean: 82.93%, range: 3.60~100.00) were the most prevalent race followed by African Americans (9.06%, 0.00~87.23) and Asian Americans (1.38%, 0.00~42.66). For socioeconomic variables, approximately 2% to 13% of the population clustered by housing units were vulnerable in terms of transportation (no vehicle, mean=6.28%, range:0~87.99), employment (unemployment rate, 5.15%, range: 0.00~27.03), education (less than high school, 13.05%, range: 1.12~73.56), and language (limited English proficiency: not well or not at all, 1.69%, range: 0.00~34.44). In addition, the population living below the federal poverty line in the past 12 months was 15.11% (2.43~55.45).

For biophysical variables, the mean temperature was  $11.25^{\circ}$ C, the mean relative humidity 67.43% and the mean diurnal temperature variation  $11.89^{\circ}$ C. These variables ranged from  $-0.01^{\circ}$ C to  $24.81^{\circ}$ C (mean temperature), from 21.94% to 84.59% (relative humidity) and from  $6.13^{\circ}$ C to  $20.19^{\circ}$ C (diurnal temperature variation). For COVID-19 health outcomes, there were on average roughly 10,000 confirmed cases and 200 deaths at the county level.

# The association between total immigrants/independent variables and COVID-19 health outcomes

Table 2 represents total impacts and 95% CIs for fifteen independent variables on both the number of confirmed cases and deaths. We found negative associations between confirmed cases and the proportion of total immigrants (-48.1, -91.5~-15.3) and Hispanic Americans (-15.2, -25.7~-2.4). This relationship suggests that an increase in the proportion of total immigrants and Hispanic Americans lowered the number of cases. Four demographic factors, including population density (total impact: 0.3, 95% CI: 0.0~0.6), the proportion of people under 18 years of age (227.7, 162.4~287.1), African American (19.6, 12.1~28.4), and other races (100.0, 79.9~121.4) were also positively associated with the number of confirmed cases. These results indicate that a one unit increase in those variables raises the number of confirmed cases by 0.3 for population density (unit: people per km<sup>2</sup>), 227.7 for those under 18 years (unit: %), 19.6 for African American (unit: %) and 100.0 for other races (unit: %). For example, a 1000 person increase in population density raises the expected number of cases by 300. A 1% increase in the proportion of people under 18 years old, African American and other races would increase the expected number of cases by 227.7, 19.6, and 100.0, respectively.

For socioeconomic variables, the proportion of households without vehicles (115.1,  $58.6 \sim 187.9$ ) and those with education less than high school (198.5,  $169.9 \sim 226.4$ ) were positively associated with confirmed cases, whereas the unemployment rate (-498.5, - 575.5 - 422.7) had a negative association with confirmed cases. For biophysical variables, we observed positive relationships between confirmed cases and two biophysical variables: relative humidity (125.7,  $106.1 \sim 143.0$ ) and diurnal temperature variation (540.7,  $460.2 \sim 622.4$ ).

Variable	Confirmed cases		Dea	Deaths	
	Total impact	CI (2.5~97.5%)	Total impact	CI (2.5~97.5%)	
Total immigrants	-48.1*	-91.5~-15.3	-5.6*	-6.8~-4.4	
Demographic variables					
Population density	0.3*	0.0~0.6	0.0	0.0~0.0	
Under 18 years	227.7*	162.4~287.1	10.0*	8.5~11.4	
Over 65 years	33.9	$-14.5 \sim 77.0$	9.3*	8.1~10.6	
Hispanic American	-15.2*	$-25.7 \sim -2.4$	0.7*	0.4~1.0	
African American	19.6*	12.1~28.4	1.9*	1.7~2.2	
Asian American	-79.6	-151.9~15.1	5.2*	3.6~7.7	
Other races	100.0*	79.9~121.4	1.8*	1.1~2.4	
Socioeconomic variables					
No vehicle	115.1*	58.6~187.9	12.7*	11.0~14.2	
Poverty	-36.3	-71.8~12.6	-4.6*	-5.4~-3.6	
Unemployment	-498.5*	$-575.5 \sim -422.7$	-11.0*	-13.2~-9.0	
Education less than high school	198.5*	169.9~226.4	7.7*	7.0~8.4	
Biophysical variables					
Mean temperature	-4.5	$-29.7 \sim 22.5$	0.9*	0.2~1.6*	
Relative humidity	125.7*	106.1~143.0*	3.2*	2.7~3.5*	
Diurnal temperature variation	540.7*	460.2~622.4*	20.8*	18.1~23.3*	

Table 2. Model coefficients and 95% confidence interval.

\*Significant values at the P=0.05 level. CI, confidence interval.

We observed similar relationships between the fifteen independent variables and the number of deaths except for Hispanic Americans. The proportion of total immigrants (-5.6, -6.8~-4.4) was the only variable that showed a negative association with deaths. All the other demographic factors covering the proportion of those under 18 years (10.0,  $8.5 \sim 11.4$ ), those over 65 years (9.3, 8.1~10.6), Hispanic American (0.7, 0.4~1.0), African American (1.9, 1.7~2.2), Asian American (5.2, 3.6~7.7) and other races (1.8,  $1.1 \sim 2.4$ ) were positively associated with the number of deaths. For socioeconomic and biophysical variables, we found similar positive relationships with deaths. The proportion of households without vehicles  $(12.7, 11.0 \sim 14.2)$ , those with education less than high school (7.7, 7.0~8.4), mean temperature (0.9, 0.2~1.6), relative humidity  $(3.2, 2.7 \sim 3.5)$  and diurnal temperature variation  $(20.8, 2.7 \sim 3.5)$ 18.1~23.3) all increased the number of deaths. On the other hand, poverty (-4.6, -5.4~-3.6) and unemployment rate (-11.0, -13.2~-9.0) showed a negative relationship with death.

# The association between sub-immigrant groups and COVID-19 health outcomes

We repeated the same analysis as above with twenty sub-immigrant groups at the continent and sub-continent level. Here, we only report the coefficients and 95% CIs of sub-immigrant groups since we did not find any significant differences in coefficients of demographic, socioeconomic, and biophysical variables among different sub-immigrant groups (Table 3). Readers can refer to Supplementary Tables 5-24 for complete coefficients and 95% CIs on all variables.





At the continent level, most of sub-immigrant groups were negatively associated with confirmed cases (Asia: -260.4, -355.3~-168.1; Europe: -731.0, -978.1~-457.3) and deaths (Americas: -7.3, -8.8~-5.7; Europe: -7.3, -13.2~-0.3; Oceania: -223.3, -270.1~185.1). Only Oceania (1303.1, 211.4~2454.9) had a positive relationship with confirmed cases. At the sub-continent level, the proportion of immigrants from Eastern Africa (-877.1, -1568.1~254.3), Northern America (-3809.0, -4313.0~3376.5), Eastern Asia (-755.9, -1212.0~-272.7), South-Central Asia (-530.0, -880.7~-192.6), Northern Europe (-6741.5, -7682.0~-6040.9) and Western Europe (-4684.5, -5427.5~-3851.9) was negatively associated with the number of confirmed cases. On the other hand, the proportion of immigrants from Southern Africa (5008.4,1525.8~8569.5), South-Eastern Asia (761.1, 345.8~1089.6) and Southern Europe (455.8, 30.6~907.8) had positive relationships with confirmed cases.

For the number of deaths, most of the sub-continent groups in Africa (Eastern Africa: -18.6, -38.3—2.9; Northern Africa: -146.5, -285.5—20.1; Middle Africa: -622.6, -801.4—464.5) and the Americas (Northern America: -90.5, -106.1—73.8; Latin America: -6.8, -8.1—5.2) had negative relationships except for Southern Africa (167.0, 77.3~269.5), while most of those in Asia (Eastern Asia: 21.0, 7.7~36.2; Western Asia: 42.5, 16.9~68.8; and South-Central Asia: 26.6, 15.5~36.9) had positive relationships except for South-Eastern Asia (-14.8, -29.2—0.2). In Europe, Northern (-176.5, -202.6—147.6) and Western Europe (-159.7, -187.3—136.2) had negative relationships, while Southern (34.0, 20.1~46.1) and Eastern Europe (34.5, 19.8~49.8) had positive relationships with deaths.

Population	Confirmed cases				Deaths			
	Total impact	CI (2.5~97.5%)	Pseudo-R <sup>2</sup>	Total impact	CI (2.5~97.5%)	Pseudo-R <sup>2</sup>		
Africa (%)	-171.1	-482.9~88.0	0.56	3.1	-7.7~14.1	0.43		
Eastern Africa (%)	-877.1*	-1568.1~-254.3	0.56	-18.6*	-38.3~-2.9	0.43		
Western Africa (%)	4536.2	-7535.9~15962.4	0.56	-184.0	$-541.4 \sim 152.6$	0.43		
Southern Africa (%)	5008.4*	1525.8~8569.5	0.56	167.0*	77.3~269.5	0.43		
Northern Africa (%)	-2656.0	$-7354.3 \sim 1535.1$	0.56	-146.5*	$-285.5 \sim -20.1$	0.43		
Middle Africa (%)	1657.1	$-4988.2 \sim 8587.6$	0.56	-622.6*	-801.4~-464.5	0.43		
Americas (%)	-24.8	$-74.5 \sim 22.1$	0.56	-7.3*	$-8.8 \sim -5.7$	0.43		
Northern America (%)	-3809.0*	-4313.0~-3376.5	0.56	-90.5*	$-106.1 \sim -73.8$	0.43		
Latin America (%)	-11.9	$-57.8 \sim 30.0$	0.56	-6.8*	$-8.1 \sim -5.2$	0.43		
Asia (%)	-260.4*	-355.3~-168.1	0.56	1.5	-0.3~4.4	0.43		
Eastern Asia (%)	-755.9*	$-1212.0 \sim -272.7$	0.56	21.0*	$7.7 \sim 36.2$	0.43		
Western Asia (%)	-974.0	$-1904.3 \sim 30.2$	0.56	42.5*	16.9~68.8	0.43		
South-Central Asia (%)	-530.0*	$-880.7 \sim -192.6$	0.56	26.6*	15.5~36.9	0.43		
South-Eastern Asia (%)	761.1*	345.8~1089.6	0.56	-14.8*	$-29.2 \sim -0.2$	0.43		
Europe (%)	-731.0*	$-978.1 \sim -457.3$	0.56	-7.3*	$-13.2 \sim -0.3$	0.43		
Northern Europe (%)	-6741.5*	$-7682.0 \sim -6040.9$	0.56	$-176.5^{*}$	$-202.6 \sim -147.6$	0.43		
Western Europe (%)	-4684.5*	$-5427.5 \sim -3851.9$	0.56	-159.7*	$-187.3 \sim -136.2$	0.43		
Southern Europe (%)	455.8*	30.6~907.8	0.56	34.0*	20.1~46.1	0.43		
Eastern Europe (%)	-411.7	-819.8~123.8	0.56	34.5*	19.8~49.8	0.43		
Oceania (%)	1303.1*	211.4~2454.9	0.56	-223.3*	$-270.1 \sim -185.1$	0.43		

# Table 3. Model coefficients and 95% confidence interval.

\*Significant values at the P=0.05 level. CI, confidence interval.





#### Discussion

This study found that the total proportion of immigrants is negatively associated with the number of confirmed cases and related deaths. We suspect this is because they are less likely to use health care facilities or resources when the symptoms are mild. In the US, immigrants are overall younger and healthier than US-born residents (Okie, 2007). Younger adults are less likely to develop severe symptoms than older adults (Snape and Viner, 2020), so they may be less likely to visit hospitals or emergency rooms. Borjas (2020) supports this idea by finding a positive relationship between the percentage of immigrants and the number of tests per 100,000 people. Immigrants also spend less money on health services (Stimpson et al., 2013). In addition, multiple barriers such as limited English proficiency, lack of health insurance, fears of deportation and complex US health care systems impose challenges on immigrants' use of health care services. COVID-19 has even raised these barriers. Currently, in-person interpreters are not common, and clinical staffs avoid using telephone interpreters due to not wanting to touch the room telephone and contaminate their own device (Ross et al., 2020). In addition, the revised public charge rules implemented in February 2020, which expand the conditions under which the government can deny immigrants admission to the US-based on the use of public services, may further discourage their use of healthcare services (Ross et al., 2020).

At the continent and sub-continent levels, we consistently found negative relationships between the number of confirmed cases and the proportion of immigrant groups by original nativity. On the other hand, we found mixed associations between the number of deaths and the proportion of immigrants. The proportion of immigrants from Africa and the Americas had negative associations, whereas the proportion of immigrants from Asia showed a positive relationship with deaths. Europe had mixed results having positive relationships with Southern and Eastern Europe and negative relationships with Northern and Western Europe. We think these regional differences are related to at least two factors within sub-immigrant groups. The first factor is different age distributions. Each sub-immigrant group has a different age structure. For example, immigrants from Latin America are relatively younger compared to sub-immigrant groups from Europe, North America, and Asia. In 2018, immigrants from Europe (median age: 53 years), and Canada (median age: 54 years) tended to be older than those from Mexico (median age: 43 years) (Budiman et al., 2020). Immigrants from Asia (median: 46 years) were slightly older than those from Latin America in 2019 (Migration Policy Institute, 2021). This may partially explain positive relationships between the proportion of immigrants from Europe and Asia and deaths.

In addition, different ratios between noncitizens and naturalized citizens by continent or sub-continent could also impact the relationships because this study was based on the combined number of non-citizens and naturalized immigrants. Generally, naturalized citizens are older than noncitizens (USA Facts, 2020). More than 60% of the total noncitizen population was between 18 and 34 years old in 2019 (Baker, 2021), whereas 65% of naturalized citizens were aged 45 or older in 2018 (USA Facts, 2020). The higher the proportion of naturalized citizens, the higher the average age and higher mortality rates. In 2019, 61% of the immigrants from Asia were naturalized citizens, which is significantly higher than the national average (52% of all immigrants) (Migration Policy Institute, 2021). We also believe other regional factors such as culture and social norms could be highly associated with COVID-19 infection rates and deaths by impacting behavioural patterns (Huynh, 2020).

We also found significant relationships between several demographic variables and COVID-19 health outcomes. Our result shows that older adults (>65) are positively associated with the number of deaths. This result can be supported by previous papers (Garg et al., 2020). In general, older adults are more likely to have underlying chronic diseases such as hypertension and diabetes (Calderón-Larrañaga et al., 2020). In addition, they have a relatively weaker immune system (Khademi et al., 2020). Several other factors such as residential environment (e.g., rest homes and nursing homes), limited access to new information from media (e.g., social media) and limited access to health services and support may increase their vulnerability (Petretto and Pili, 2020). We also found that the proportion of those under 18 years old is positively associated with confirmed cases and death. This result aligned with Karmakar et al. (2021), who report higher COVID-19 confirmed cases (incidence rate ratios: 1.07, 95% CI: 1.08-1.10) and mortality rates (1.05, 1.04-1.07) for those under 17 years old with a county-level analysis. Even though this age group is less likely to develop severe symptoms, they seem to play an important role in spreading the virus (Anderson et al., 2021). They also have a significantly greater amount of the virus in the nose, which can facilitate transmission (Heald-Sargent et al., 2020).

Additionally, we found that the proportion of Hispanic Americans, African Americans, Asian Americans, and other races (American Indian, Alaska Native, Native Hawaiian and other pacific islander) are positively associated with the number of deaths. Karmakar et al. (2021) report higher mortality rates among African Americans (incidence rate ratios: 1.02; 95% CI, 1.02-1.03), Hispanics (1.02; 1.01-1.02), American Indians or Alaskan Natives (1.02; 1.02-1.03) and Asians (1.01; 0.99~1.03). Hatcher et al. (2020) also show that American Indians and Alaska Natives have 3.5 times more cases than Whites. Some studies point out the importance of physiological differences among different racial and ethnic groups (Evans and Lippman, 2020), however, we think that these disparities are more related to socioeconomic status, such as housing conditions (Ahmad et al., 2020) and household size (Liu et al., 2021). Precarious work and adverse working conditions among minority groups increases the risk of infections as well (Paremoer et al., 2021). These factors may raise the number of interactions among people and subsequently increase the risk of COVID-19 infection.

Finally, we found that counties with a high proportion of the population without vehicles or a high school diploma have higher confirmed cases and death. These variables are highly associated with the level of income and health. Multiple papers point out the importance of these socioeconomic variables for increasing or decreasing the risk of COVID-19 infection (e.g., Hawkins et al., 2020). However, we found a negative relationship between the unemployment rate and COVID-19 health outcomes. We suspect that unemployed people face several barriers to accessing COVID-19 testing and treatment services due to limited health insurance coverage (Calderón-Larrañaga et al., 2020; Tolbert et al., 2020). Even though the Families First Coronavirus Response Act (FFCRA) covers all medical cost-sharing associated with testing services, patients are still responsible for treatment costs until they reach their out-of-pocket maximum (King, 2020). In addition, unemployed men are less physically active than employed men, which may lower the likelihood of COVID-19 infection (Van Domelen et al., 2011).

There are at least three limitations in this study. First, COVID-19 health outcome data could introduce some uncertainty and error while collecting data. For example, the data might not exactly match a patient's actual residency location. A person registered in county A might live or work in county B. Second, health outcome data may only include some of the actual number of confirmed cases and mortalities. Pelizza et al. (2021) pointed out that the health outcomes of undocumented people would not be well captured in official statistics. According to Passel and Cohn (2019), there were 10.5 million undocumented people in the US in 2017, accounting for 3.2% of the total US population. These people seem more vulnerable to COVID-19 than other groups due to their limited financial ability and access to healthcare services even though their ages tend to be younger than US natives. Such errors may weaken the relationship between health outcomes and variables used in this study. Third, we used the combined number of immigrants, including naturalized immigrants and noncitizens. These two groups appear to have different socioeconomic and demographic characteristics. Naturalized immigrants are older, more educated, and have relatively better socioeconomic status than non-citizens (Passel, 2005). Non-citizens also cover a wide range of subgroups including international students, temporary agricultural workers, exchange visitors and other different groups. This large variation within immigrant subgroups may increase errors in the analysis.

#### Conclusions

It is clear that immigrants, who make up more than 10% of the total US population, are an important part of the country. The success of reducing COVID-19 mortality and morbidity depends on the cooperation of all community members through community vaccination and massive testing programs (Al Awaidy and Khamis, 2020; Mohammadi et al., 2021; Mollalo et al., 2021; Yamey et al., 2020). We need to ensure that all communities have equal access to COVID-19 resources. Messages and guidelines for tests and vaccines in multiple languages according to the community demographics may help those who are linguistically isolated (Wild et al., 2020). Reducing public assistance restrictions and amending the public charge rules could increase the rate of testing and vaccinations of immigrants as well (Langellier, 2020). We hope these measures help mitigate the impact of COVID-19 on the health of the public. There are a couple of future research opportunities. Even though this study was based on the total number of immigrants combining both non-citizens and naturalized citizens due to data availability, future research should focus only on noncitizens. As showed in the introduction, these two immigrant groups tend to have significantly different socioeconomic characteristics. Including naturalized citizens in the analysis may dilute the associations to the COVID-19 health outcomes. In addition, the relationships between immigrants and COVID-19 health outcomes could be different by region. For example, rural regions are more likely to need low-skilled immigrants for agricultural work, whereas urban regions would be more likely to need high-skilled immigrants. Combining these two areas in the analysis would increase errors and uncertainty. Therefore, future research should separately investigate the relationship by region. Furthermore, it would be worthwhile to investigate what factors are associated with the different relationships between sub-immigrant groups and COVID-19 health outcomes.

## References

- Ahmad K, Erqou S, Shah N, Nazir U, Morrison AR, Choudhary G. Wu W-C, 2020. Association of poor housing conditions with COVID-19 incidence and mortality across US counties. PloS One 15:11.
- Al Awaidy ST, Khamis F, 2020. Preparing the community for a vaccine against COVID-19. Oman Med J 35:6.
- Anderson EJ, Campbell JD, Creech CB, Frenck R, Kamidani S, Munoz FM, Nachman S, Spearman P, 2021. Warp Speed for Coronavirus Disease 2019 (COVID-19) Vaccines: Why Are Children Stuck in Neutral? Clin Infect Dis 73:336-40.
- Anselin L, 1988. Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. Geogr Anal 20:1-17.
- Baker B, 2021. Population estimates of nonimmigrants residing in the United States: Fiscal Years 2017-2019. Available from: https://www.dhs.gov/sites/default/files/publications/immigration-statistics/Pop\_Estimate/NI/ni\_population\_estimates\_fiscal\_years\_2017\_-2019v2.pdf
- Bhadra A, Mukherjee A, Sarkar K, 2021. Impact of population density on Covid-19 infected and mortality rate in India. Model Earth Syst Environ 7:623-9.
- Borjas GJ, 2020. Demographic determinants of testing incidence and COVID-19 infections in New York city neighborhoods. HKS Working Paper No. RWP20-008. Available from: https://doi.org/10.2139/ssrn.3572329
- Budiman A, Tamir C, Mora L, Noe-Bustamente L, 2020. Facts on U.S. immigrants, 2018. Pew Research Center, USA. Available from: https://www.pewresearch.org/hispanic/2020/08/20/ facts-on-u-s-immigrants/
- Calderón-Larrañaga A, Dekhtyar S, Vetrano DL, Bellander T, Fratiglioni L, 2020. COVID-19: risk accumulation among biologically and socially vulnerable older populations. Ageing Res Rev 63:101149.
- Czeisler MÉ, Garcia-Williams AG, Molinari N-A, Gharpure R, Li Y, Barrett CE, Robbins R, Facer-Childs ER, Barger LK, Czeisler CA, Rajaratnam SNW, Howard ME, 2020. Demographic characteristics, experiences, and beliefs associated with hand hygiene among adults during the COVID-19 pandemic - United States, June 24-30, 2020. MMWR Morb Mortal Wkly Rep 69:1485-91.
- Daly C, Smith JW, Smith JI, McKane RB, 2007. High-resolution spatial modeling of daily weather elements for a catchment in the Oregon Cascade Mountains, United States. J Appl Meteorol Climatol 46:1565-86.
- Elhorst JP, 2010. Applied spatial econometrics: raising the bar. Spat Econ Anal 5:9-28.
- Evans RM, Lippman SM, 2020. Shining light on the COVID-19 pandemic: a vitamin D receptor checkpoint in defense of unregulated wound healing. Cell Metab 32:704-9.
- Garg S, Kim L, Whitaker M, O'Halloran A, Cummings C, Holstein R, Prill M, Chai SJ, Kirley PD, Alden NB, Kawasaki B, Yousey-Hindes K, Niccolai L, Anderson EJ, Openo KP, Weigel A, Monroe ML, Ryan P, Henderson J, Kim S, Como-Sabetti K, Lynfield R, Sosin D, Torres S, Muse A, Bennett NM, Billing L, Sutton M, West N, Schaffner W, Talbot HK, Aquino C, George A, Budd A, Brammer L, Langley G, Hall AJ, Fry A, 2020. Hospitalization rates and characteristics of patients hospitalized with laboratory-confirmed coronavirus disease 2019 COVID-NET, 14 States, March 1-30, 2020. MMWR Morb Mortal Wkly Rep 69:458-64.





- Golestaneh L, Neugarten J, Fisher M, Billett HH, Gil MR, Johns T, Yunes M, Mokrzycki MH, Coco M, Norris KC, Perez HR, Scott S, Kim RS, Bellin E, 2020. The association of race and COVID-19 mortality. E Clin Med 25:100455.
- Griffith DA, 1987. Spatial autocorrelation: a primer. Resource Publications in Geography. The Association of American Geographers, Washington, DC, USA.
- Hamidi S, Sabouri S, Ewing R, 2020. Does density aggravate the COVID-19 pandemic? Early findings and lessons for planners. J Am Plann Assoc 86:495-509.
- Hanson GH, Kerr WR, Turner S, 2018. High-skilled migration to the United States and its economic consequences. University of Chicago Press, Chicago, IL, USA.
- Hatcher SM, Agnew-Brune C, Anderson M, Zambrano LD, Rose CE, Jim MA, Baugher A, Liu GS, Patel SV, Evans ME, Pindyck T, Dubray CL, Rainey JJ, Chen J, Sadowski C, Winglee K, Penman-Aguilar A, Dixit A, Claw E, Parshall C, Provost E, Ayala A, Gonzalez G, Ritchey J, Davis J, Warren-Mears V, Joshi S, Weiser T, Echo-Hawk A, Dominguez A, Poel A, Duke C, Ransby I, Apostolou A, McCollum J, 2020. COVID-19 among American Indian and Alaska native persons 23 states, January 31-July 3, 2020. MMWR Morb Mortal Wkly Rep 69:1166-9.
- Hawkins RB, Charles EJ, Mehaffey JH, 2020. Socio-economic status and COVID-19–related cases and fatalities. Public Health 189:129-34.
- Heald-Sargent T, Muller WJ, Zheng X, Rippe J, Patel AB, Kociolek LK, 2020. Age-related differences in nasopharyngeal severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) levels in patients with mild to moderate coronavirus disease 2019 (COVID-19). JAMA Pediatr 174:902-3.
- Horner KM, Wrigley-Field E, Leider JP, 2021. A First Look: Disparities in COVID-19 Mortality Among US-Born and Foreign-Born Minnesota Residents. Popul Res Policy Rev 1-14.
- Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J, Gu X, Cheng Z, Yu T, Xia J, Wei Y, Wu W, Xie X, Yin W, Li H, Liu M, Xiao Y, Gao H, Guo L, Xie J, Wang G, Jiang R, Gao Z, Jin Q, Wang J, Cao B, 2020. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. The lancet 395:497-506.
- Huynh TLD, 2020. Does culture matter social distancing under the COVID-19 pandemic? Saf Sci 130:104872.
- Jamil T, Alam I, Gojobori T, Duarte CM, 2020. No evidence for temperature-dependence of the COVID-19 epidemic. Front Public Health 8:436.
- Johns Hopkins Coronavirus Resource Center. Available from: https://coronavirus.jhu.edu/map.html\_Accessed: March 28, 2021.
- Jones A, Grigsby-Toussaint DS, 2020. Housing stability and the residential context of the COVID-19 pandemic. Cities Health 1-3.
- Karmakar M, Lantz PM, Tipirneni R, 2021. Association of social and demographic factors with COVID-19 incidence and death rates in the US. JAMA Netw Open 4:1.
- Khademi F, Moayedi S, Golitaleb M, karbalaie N, 2020. The COVID□19 pandemic and death anxiety in the elderly. Int J Ment Health Nurs [Epub ahead of print].
- King JS, 2020. Covid-19 and the need for health care reform. N Engl J Med 382.
- Langellier BA, 2020. Policy recommendations to address high risk of COVID-19 among immigrants. Am J Public Health 110:8.
- LeSage J, Pace RK, 2009. Introduction to spatial econometrics. Chapman and Hall/CRC, Boca Raton, FL, USA.

- Liu P, McQuarrie L, Song Y, Colijn C, 2021. Modelling the impact of household size distribution on the transmission dynamics of COVID-19. J R Soc Interface 18:20210036.
- Ludvigsson JF, 2020. Systematic review of COVID□19 in children shows milder cases and a better prognosis than adults. Acta Paediatr 109:1088-95.
- Ma Y, Zhao Y, Liu J, He X, Wang B, Fu S, Yan J, Niu J, Zhou J, Luo B, 2020. Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. Sci Total Environ 724:138226.
- Mansfiled ER, Helms BP, 1982. Detecting multicollinearity. Am Stat 36:158-60.
- Manski CF, 1993. Identification of endogenous social effects: The reflection problem. Rev Econ Stud 60:531-42.
- Migration Policy Institute, 2021. Immigrants from Asia in the United States. Available from: https://www. migrationpolicy.org/article/immigrants-asia-united-states-2020
- MohammadEbrahimi S, Mohammadi A, Bergquist R, Dolatkhah F, Olia M, Tavakolian A, Pishgar E, Kiani B, 2021. Epidemiological characteristics and initial spatiotemporal visualisation of COVID-19 in a major city in the Middle East. BMC Public Health 21:1-18.
- Mohammadi A, Mollalo A, Bergquist R, Kiani B, 2021. Measuring COVID-19 vaccination coverage: an enhanced age-adjusted two-step floating catchment area model. Infect Dis Poverty 10:118.
- Mollalo A, Mohammadi A, Mavaddati S, Kiani B, 2021. Spatial Analysis of COVID-19 Vaccination: A Scoping Review. Int J.Environ Res Public Health 18:12024.
- Mutambudzi M, Niedwiedz C, Macdonald EB, Leyland A, Mair F, Anderson J, Celis-Morales C, Cleland J, Forbes J, Gill J, Hastie C, Ho F, Jani B, Mackay DF, Nicholl B, O'Donnell C, Sattar N, Welsh P, Pell JP, Katikireddi SV, Demou E, 2021. Occupation and risk of severe COVID-19: prospective cohort study of 120 075 UK Biobank participants. Occup Environ Med 78:307-14.
- Okie S, 2007. Immigrants and Health Care At the Intersection of Two Broken Systems. N Engl J Med 357:525-9.
- Ong SWX, Tan YK, Chia PY, Lee TH, Ng OT, Wong MSY, Marimuthu K, 2020. Air, surface environmental, and personal protective equipment contamination by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) from a symptomatic patient. JAMA 323:1610-2.
- Paremoer L, Nandi S, Serag H, Baum F, 2021. Covid-19 pandemic and the social determinants of health. BMJ 372.
- Passel JS, 2005. Unauthorized migrants: Numbers and characteristics. Pew Hispanic Center Washington, DC, USA. Available from: https://www.pewresearch.org/hispanic/2005/06/14/ unauthorized-migrants/
- Passel JS, Cohn D, 2019. Mexicans decline to less than half the US unauthorized immigrant population for the first time. Pew Research Center Washington, DC, uSA. Available from: https://www.pewresearch.org/fact-tank/2019/06/12/us-unau-thorized-immigrant-population-2017/
- Paul RK, 2006. Multicollinearity: Causes, effects and remedies. IASRI New Delhi 1:58-65.
- Pelizza A, Milan S, Lausberg Y, 2021. The dilemma of undocumented migrants invisible to COVID-19 counting. COVID-19 From The Margins 70-8.
- Petretto DR, Pili R, 2020. Ageing and COVID-19: what is the role





for elderly people? Geriatrics 5:25.

- Pica N, Bouvier NM, 2012. Environmental factors affecting the transmission of respiratory viruses. Curr Opin Virol 2:90-5.
- Prata DN, Rodrigues W, Bermejo PH, 2020. Temperature significantly changes COVID-19 transmission in (sub) tropical cities of Brazil. Sci Total Environ 729:138862.
- Qi H, Xiao S, Shi R, Ward MP, Chen Y, Tu W, Su Q, Wang W, Wang X, Zhang Z, 2020. COVID-19 transmission in Mainland China is associated with temperature and humidity: a timeseries analysis. Sci Total Environ 728:138778.
- Ross J, Diaz CM, Starrels JL, 2020. The disproportionate burden of COVID-19 for immigrants in the Bronx, New York. JAMA Intern Med 180:1043-4.
- Rutter PD, Mytton OT, Mak M, Donaldson LJ, 2012. Socio-economic disparities in mortality due to pandemic influenza in England. Int J Public Health 57:745-50.
- Snape MD, Viner RM, 2020. COVID-19 in children and young people. Science 370:286-8.
- Stimpson JP, Wilson FA, Su D, 2013. Unauthorized immigrants spend less than other immigrants and US natives on health care. Health Aff 32:1313-8.
- Tolbert J, Orgera K, Damico A, 2020. Key facts about the uninsured population. Kaiser Family Foundation. 2019. Available from: https://www.kff.org/uninsured/issue-brief/key-factsabout-the-uninsured-population/view/footnotes/
- U.S. Census Bureau ACS, 2019. Available from: https://www.census.gov/programs-surveys/acs

- USA Facts, 2020. Immigration demographics: A look at the native and foreign-born populations. Available from: https://usafacts.org/articles/immigration-demographics-looknative-and-foreign-born-populations/
- Vallejo JA, Keister LA, 2020. Immigrants and wealth attainment: migration, inequality, and integration. J Ethn Migr 46:3745-61.
- Van Domelen DR, Koster A, Caserotti P, Brychta RJ, Chen KY, McClain JJ, Troiano RP, Berrigan D, Harris TB, 2011. Employment and physical activity in the US. Am J Prev Med 41:136-45.
- Van Doremalen N, Bushmaker T, Munster VJ, 2013. Stability of Middle East respiratory syndrome coronavirus (MERS-CoV) under different environmental conditions. Eurosurveillance 18:20590.
- Wild A, Kunstler B, Goodwin D, Onyala S, Zhang L, Kufi M, Salim W, Musse F, Mohideen M, Asthana M, Al-Khafaji M, Geronimo MA, Coase D, Chew E, Micallef E, Skouteris H, 2020. Communicating COVID-19 health information to culturally and linguistically diverse (CALD) communities: the importance of partnership, co-design, and behavioural and implementation science.
- Xie J, Zhu Y, 2020. Association between ambient temperature and COVID-19 infection in 122 cities from China. Sci Total Environ 724:138201.
- Yamey G, Schäferhoff M, Hatchett R, Pate M, Zhao F, McDade KK, 2020. Ensuring global access to COVID-19 vaccines. Lancet 395:1405-6.