Estimating older adult mortality from COVID-19

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Abstract

Objective

The purpose of this study was to employ simulations to model the probability of mortality from COVID-19 (i.e., coronavirus) for older adults in the United States (U.S.) given at best and at worst cases.

Methods

This study first examined current epidemiological reports to better understand the risk of mortality from COVID-19. Past epidemiological studies from severe acute respiratory syndrome or SARS were also examined given similar virology. Next, at best and at worst mortality cases were considered with the goal of estimating the probability of mortality. To accomplish this for the general population, microdata from the National Health Interview Survey pooled sample (2016, 2017, and 2018 IPUMS NHIS with a sample of 34,881 adults at least 60 years of age) were utilized. Primary measures included age and health status (diabetes, body mass index, and hypertension). A logit regression with 100,000 simulations was employed to derive the estimates and probabilities.

Results

Age exhibited a positive association for the probability of death with an odds ratio (OR) of 1.22 (p<0.05, 1.05-1.42, 95% C.I.). A positive association was also found for obesity (OR 1.03, p<0.01, 1.02-1.04 95% C.I.) and hypertension (OR 1.36, p<0.01, 1.09-1.66 95% C.I.) for the at best case. Diabetes was significant but only for the at best case.

Discussion

This study found mortality increased with age and was notable for the 74-79 age group for the at best case and the 70-79 age group of the at worst case. Obesity was also important and suggested a higher risk for mortality. Hypertension also exhibited greater risk but the increase was minimal. Given the volume of information and misinformation, these findings can be applied by health professionals, gerontologists, social workers, and local policymakers to better inform older adults about mortality risks and, in the process, re-establish public trust.

Keywords: Health promotion, Population aging, Successful aging
The healthcare community continues to work vigorously towards a better understanding of severe acute respiratory syndrome coronavirus 2 or SARS-CoV-2 (i.e., coronavirus or COVID-19). As of August 30, 2020, nearly 25.1 million cases had been confirmed with approximately 843,000 deaths globally. In the United States (U.S.), almost 5.9 million cases had been confirmed with approximately 183,000 deaths. Early work derived global approximations for mortality at 2.5% with the conclusion that higher estimates were primarily observed among men and older adults (Jin et al., 2020; Wang, Tang, & Wei, 2020; Wortham et al., 2020). Although the evolving nature of how this virus impacts and disrupts the pathophysiology of humans now suggests children and young adults may also be at-risk, most clinical and epidemiological findings still report older adults and adults with pre-existing health conditions to be at greater risk for mortality (CDC & Bialek et al., 2020; CDC & Chow et al., 2020). While these more recent studies appear to reach consensus in better identifying at-risk groups and higher-quality data gathering and reporting standards have been slowly instituted at testing sites, mortality estimates continue to be reported with a wide range, as one study approximated 8% while another estimated 15% (Lachmann, 2020; Lai et al., 2020; Rajor et al., 2020; Zhou et al., 2020). A different study and one which examined only U.S. patients in a hospital setting in New York estimated an overall mortality rate of 26% for adults older than 65 years of age and this increased to approximately 35% for age group 70-79 and nearly 50% for age group 80-89 (Richardson et al., 2020). A more recent analysis by the Centers for Disease Control and Prevention or CDC estimated the mortality percentage for confirmed cases at 2.7% for age group 65-74, 4.3% for age group 75-84, and 10.4% for age 85 and older. Given these broad estimates surrounding fatality for patients in a clinical setting, providing older adults with a simpler understanding of the likelihood of mortality (in addition to fatality) based on different at best and at worst cases can help this group better understand their risk. Taking into consideration both the wide-spread misinformation and newly released safety measures surrounding the coronavirus (e.g., consumption of certain food products to prevent the virus, value of lockdowns and social distancing, six
new symptoms added by CDC near the end of April 2020, three new symptoms added by the CDC during the middle of July 2020, etc.), effectively communicating risk by presenting easy-to-understand at best/at worst cases also has the potential to gain public trust and increase safety compliance with the older adult community (Fleming, 2020; Krause et al., 2020). This is particularly important for the U.S. because it has the highest number of confirmed cases and deaths relative to the rest of the world. In addition, political maneuvering during the initial and on-going response from key leaders has created more misinformation (Barrios & Hochberg, 2020).

Methods

Study Approach

The main purpose of this analysis was to estimate mortality risk for older adults. More specifically, what is likelihood of dying from the virus? This is an important inquiry because most studies to-date have been hospital reports or clinical studies with relatively small samples (i.e., couple hundred to a few thousand). As such, the mortality risk for the general population and the uncertainty surrounding it are less understood, particularly given widespread misinformation. To develop this analysis, the first step was to obtain mortality estimates from current and past research by utilizing (1) the COVID-19 Collection from the Journal of the American Medical Association Network, (2) the Coronavirus Resource Center from The Lancet, (3) the COVID resources website from the Centers for Disease Control and Prevention (CDC), and (4) the coronavirus resource center and tracker from Johns Hopkins University and Medicine. These sources provide the most up-to-date research relating to COVID-19 clinical cases, general demographic characteristics of infected individuals, hospital case studies, and patient outcomes. The next step was to introduce these mortality estimates into an actual dataset and one representative of the U.S. population. This was accomplished by selecting the National Health Interview Survey (see Study Population section). Third, mortality estimates were randomly
assigned to individuals and then adjusted based on age and pre-existing conditions (see Health Status section). Higher mortality was assigned based on the CDC guidelines, which identified the following characteristics as presenting higher risk: older age groups (i.e., people 65 and older), diabetes, heart conditions, and obesity (CDC, n.d.). Given the uncertainty surrounding these mortality estimates, Monte Carlo simulations were used to better understand its sampling distribution by generating many random samples from the data. In other words, drawing simulated parameters to better understand the probability distribution of the outcome (King et al., 2000).

Utilizing simulations was also a reasonable approach since the objective was to examine various scenarios (Mooney, 1997). This was accomplished by first estimating the main and secondary parameters (see Measures section). Next, the point estimate (denoted $\hat{\gamma}$) and the variance matrix (denoted $\hat{\Sigma}$) were recovered from the logistic regression, which can be formally represented as $\hat{\gamma} = \text{vec}(\hat{\beta}, \hat{\alpha})$. Lastly, one value was drawn from the estimated vector (where $\vec{\gamma} = \text{vec}(\hat{\beta}, \hat{\alpha})$) and then repeated (i.e., simulated) 100,000 times to obtain 100,000 draws of the main and secondary parameters. Although 10,000 draws would be sufficient, a larger number was selected because as the number of draws increases, the accuracy of the approximation improves. However, an increase beyond 100,000 will result in only a marginal improvement in accuracy (i.e., less than one percent) at the expense of computing time and power and will usually not be a worthwhile trade-off (Carsey & Harden, 2013; Kocak, 2019). Given the advantages inherent with large sample sizes, the central limit theorem was utilized to support the use of a multivariate normal distribution with mean $\hat{\gamma}$ and variance $\hat{\Sigma}$ as the distribution for the draws.
Study Population

This study utilized microdata from the 2016, 2017, and 2018 National Health Interview Survey (IPUMS NHIS). NHIS is a long-standing and major data collection project of the National Center for Health Statistics/Centers for Disease Control and Prevention (NCHS/CDC). It is a cross-sectional survey of a nationally representative sample, which makes it suitable for this study. The initial analytic sample contained 225,558 observations. Since the unit of analysis was older adults, a total of 189,219 observations were dropped because they were under 60 years of age. After removing “unknown” and “undefined” responses for total family income (n=3,436 and n=4,902 respectively), the sample now equaled 28,001. After removing “unknown” (n=12) and “refused” (n=85) responses for coronary heart disease and responses where body mass index or BMI was reported as 99.99 (n=1,361), the analytic sample contained 26,543 observations. Since some values were unknown/undefined for total family income, an imputation process was utilized for this variable and the final analytic sample contained 34,881 observations (see Appendix).

Measures

Dependent variable: Mortality

Mortality, the dependent variable, was based on current and past studies (CDC & Chow, 2020; Lachmann, 2020; Rajor et al., 2020). For the at best case, a 0.5% probability of mortality was randomly assigned and it increased monotonically with age until it reached 3% for age 85 years. Stated differently and in non-technical terms, a mortality distribution ranging from 0.5% to 3% was randomly assigned with a higher percentage at older ages. If the individual was selected into this category, then mortality would be assigned (i.e., mortality variable reflected as =1). If the individual was not selected into this
category, then mortality would not occur (i.e., mortality variable reflected as =0). The three percent at
the higher end was a conservative estimate since some reports suggest anywhere from four to five
percent (Richardson et al., 2020; Wang et al., 2020; Wu et al., 2020). Although the value used in this
analysis was higher than laboratory-confirmed COVID-19 mortality estimates from the Emerging
Infections Program (EIP), the EIP estimates for hospitalizations have steadily increased every week since
March 21, 2020. By year’s end, mortality estimates may slowly converge to the at best case. For those
with pre-existing health conditions, mortality was adjusted to 10% for obese individuals and 8% for
those with diabetes or hypertension (Baud et al., 2020; CDC & Chow et al., 2020; Wu et al., 2020; Yang
et al., 2006; Zhou et al., 2020). In other words, individuals with such a health condition were randomly
assigned the afore-mentioned mortality probability. If the individual was selected into this category,
then mortality variable would be assigned as =1 and if not selected, then the mortality variable would
=0. Since there currently is no framework to numerically assess additional risk from these conditions,
current case studies combined with previous research from the initial SARS served as a guideline (Baud
et al., 2020; Dietz & Santos-Burgoa, 2020). This mortality adjustment was not an additional risk (i.e.,
additive) but the overall adjustment. Based on earlier work on severe respiratory syndromes, a 3%
probability of mortality was randomly assigned and it increased monotonically with age until it reached
8% for age 85 years for the at worst case (Chen & Subbarao, 2007). Although this estimate seems high,
one should note the following: (a) this is the worst case model and (b) such an estimate may be
applicable when one considers under-reporting since early deaths were not attributed to the virus and
this recording (i.e., misclassification of deaths) possibility remains (Lachmann, 2020). For pre-existing
health conditions, mortality was once again adjusted to 10% for obese individuals and 8% for those with
diabetes or hypertension.
Types of Health Insurance

Medicaid, Medicare, and private health insurance encompassed the different types of health insurance. Medicaid provided medical assistance to low income families with children and aged/blind/permanently disabled individuals with low income; Medicare provided healthcare coverage for adults 65 years and older with at least 40 quarters (i.e., credits) of payroll taxes; private insurance was a comprehensive healthcare plan which was paid in part or fully by the employer or by the individual.

Health Status

Health status related to hypertension, body mass index (BMI), diabetes, and coronary heart disease. Hypertension signified if the respondent was diagnosed for high blood pressure by a health care professional and coded as a dummy variable. BMI was recorded as a numeric variable and calculated from the individual’s height and weight. It was used as a rough measure to assess body fat and a BMI >30 indicated obesity. Diabetes and coronary heart disease were also coded as dummy variables and indicated if the respondent was diagnosed for such a condition by a health care professional.

Demographic and Economic Characteristics

The independent variables in this category were age, gender, currently married, education, and total family income. Gender was formulated as a dummy variable where male=1 and female=0. Currently married was a binary variable and indicated if the individual was legally married at the time of the interview. Education was categorized as less than high school, high school, some college, and advanced degree with high school as the reference category. Total family income was self-reported and
based on the individual’s own income combined with that of other family members living in that household. It was categorized as less than $35k, between $35k but less than $50k, $50k but less than $75k, $75k but less than $100k, and $100k or greater with less than $35k as the reference category.

Analysis

The analysis consisted of descriptive statistics and a series of logistic regressions based on different mortality scenarios. To ensure proper design-based analyses, all three survey components were utilized: primary sampling unit weight, person weight, and strata. The logistic regression was suitable given the binary outcome values for $y = \begin{cases} 0, \text{ no mortality} \\ 1, \text{ mortality} \end{cases}$ while the matrix $X\beta$ denoted demographic, health insurance, and health status characteristics. Given that the primary objective was to estimate mortality risk for older adults, Monte Carlo simulations (i.e., 100,000 draws for each case) were employed to obtain the main and secondary parameter estimates. Since some observations were undefined/unknown for total family income, an imputation process was also employed (see Appendix). All analyses were performed using Stata V15 (StataCorp., 2017).

Specification Tests for Multicollinearity

Although the health status variables measure different characteristics, there may be a possibility of multicollinearity. To test for an association between these variables, a variance inflation factors or VIF test was conducted. Results show an overall mean VIF of 1.07 while individual values corresponded to the following: 1.10 for BMI, 1.11 for diabetes, 1.10 for hypertension, and 1.04 for coronary heart disease. VIF values greater than ten suggest the existence of multicollinearity (Mansfield & Helms, 1982; O’Brien, 2007). For this study, multicollinearity was not an issue.
Results

Descriptive Summary, Regression Analyses, and Simulations

Table 1 provides the mean descriptive measures. In terms of overall characteristics, the average age was 71 years of age with 44% male/56% female. Nearly three-fourths received Medicare and slightly more than half maintained private health insurance. While only 13% reported coronary heart disease, 24% had diabetes and 60% indicated having hypertension.

Table 2 provides the at best case (left column) and the at worst case (right column). Age was associated with increased odds (1.22, p<0.02 and 1.27, p<0.01, respectively). For both cases, the 95% confidence interval or C.I. was moderate and ranged from above one to nearly 1.45. As for health status, BMI exhibited a positive association for both cases (1.04, p<0.01 and 1.03, p<0.01, respectively). For this health condition, the 95% C.I. was narrow and ranged from 1.02-1.04. Coronary heart disease was associated with greater odds but was only significant at p<0.10 with an odds ratio of 1.12 and 1.11 for the at best and at worst cases, respectively. Diabetes also reflected a higher probability but was significant only for the at best case. Lastly, hypertension was associated with greater odds in both cases (1.36, p<0.01 and 1.19, p<0.01, respectively) and exhibited a considerable 95% C.I. range.

Discussion and conclusion

This report examined the risk of mortality for older adults from the coronavirus. Utilizing the 2016, 2017, and 2018 pooled NHIS public-use microdata files, this study found a positive association between age and mortality and this was notable at age range 74-79 for the at best case and age range 70-79 for the at worst case (see Figure 1 and Figure 2). For example, the predicted probability of mortality for the overall sample increased from approximately 3% at age 65 to nearly 16% by age 75 and
nearly 40% after age 80 for the at best case. For the at worst case, it increased from 5% at age 65 to 20% by age 75 to nearly 50% after age 80 (overall sample). [Figure 1 and Figure 2 about here]

In terms of health status, mortality risks from obesity and hypertension were evident (see Figure 1 and Figure 2). For the at best case, the probability of mortality was higher and increased steadily for obese individuals. By age 75, the predicted probability approximated 20% (or 4% higher than the overall sample) and continued to increase gradually until 80 years of age. This finding confirms clinical case reports and patient case studies, which have suggested individuals with higher BMI are at greater risk for severe illness and death (CDC & Chow et al., 2020; Dietz & Santos-Burgoa, 2020; Zhou et al., 2020). This finding also requires further investigation as to why obesity, in particular, was associated with worse outcomes. Possibly, (a) obesity combined with inflammation (due to the virus) places additional pressure on cardio-pulmonary organs and (b) wide-spread obesity in several counties throughout the U.S. may also explain why mortality from the coronavirus has been relatively higher in certain areas (Mill et al., 2020). This information can be used (1) by healthcare professionals to provide more direct care in terms of consulting and testing and (2) by local policymakers to craft tailored policies surrounding social distancing, contact tracing, and stay-at-home orders. Some examples where this would be useful include counties which share a common border with Arkansas, Louisiana, and Mississippi, counties in southwest Alabama, and counties in southeast South Carolina (i.e., places with a greater proportion of adults 65 and older with obesity). Finally, hypertension also reflected an increased probability for the at best case and this was notable for adults aged 70 and older. However, the added risk from this condition was not large for the at worst case.
Study implications: Communication efforts

The vast amount of new information, as well as misinformation (which has been referred to as *misinfodemic*), about the coronavirus may confuse older adults. Similarly, the enormous amount of past and on-going research will continue to overwhelm community health workers, gerontologists, and other healthcare professionals (O’Connor & Murphy, 2020; Saleh, 2020). This study undertook the burden of evaluating such a large body of research and then simulated mortality probabilities by utilizing a large national dataset with the goal of offering simple at best and at worst cases so older adults at varying age-groups and those with pre-existing health conditions could better understand their risk. At present, our understanding largely stems from hospital settings and clinical case studies (which have smaller sample sizes) and wide-ranging mortality estimates. Healthcare professionals could easily refer to the figures to communicate risk by age and then use the remainder of the conversation to explain why certain health conditions pose greater risk and then formulate action plans to help older adults reduce risk.

Limitations and concluding remarks

The primary limitations of this study relate to the availability of data. This can largely be attributed to the recent emergence of the virus. Additionally, the complex nature of the virus, its ease of transmission, and the economics and politics surrounding this pandemic have presented challenges which have made gathering and processing quality data more difficult. Another limitation corresponds
to a lack of geographic measures. That is, the inability to examine variables at the state or county-level. For example, a recent study found higher mortality for counties with higher particulate (i.e., PM2.5) matter (Wu et al., 2020). Another study found areas with long-term exposure to nitrogen dioxide (i.e., NO₂) with higher COVID-19 fatality. As on-going research continues to offer greater insight into how regional/local factors impact mortality, better estimates can be produced. Future research can examine how these factors (e.g., race, pollution, health professional shortage areas, local unemployment, etc.) influence mortality by conducting an analysis at the county-level.
References

Barrios, J. M., & Hochberg, Y. (2020). Risk perception through the lens of politics in the time of the covid-19 pandemic (No. w27008). National Bureau of Economic Research.

Baud, D., Qi, X., Nielsen-Saines, K., Musso, D., Pomar, L., & Favre, G. (2020). Real estimates of mortality following COVID-19 infection. The Lancet infectious diseases. doi.org/10.1016/S1473-3099(20)30195-X

Bodner, T. E. (2008). What improves with increased missing data imputations? Structural Equation Modeling: A Multidisciplinary Journal, 15(4), 651-675. doi.org/10.1080/10705510802339072

Carsey, T. M., & Harden, J. J. (2013). Monte Carlo simulation and resampling methods for social science. Sage Publications.

CDC. (n.d.). Coronavirus (COVID-19). U.S. Department of Health and Human Services. Retrieved June 30, 2020, from https://www.cdc.gov/coronavirus/2019-ncov/index.html

CDC & Bialek, S., Gierke, R., Hughes, M., & Skoff, T. (2020). Coronavirus Disease 2019 in Children—United States, February 12–April 2, 2020. MMWR. Morbidity and Mortality Weekly Report, 69(14), 422. doi: 10.15585/mmwr.mm6914e4
CDC & Chow, N., Fleming-Dutra, K., Gierke, R., & Roguski, K. (2020). Preliminary estimates of the prevalence of selected underlying health conditions among patients with coronavirus disease 2019—United States, February 12–March 28, 2020. Morbidity and Mortality Weekly Report, 69(13), 382. doi:10.15585/mmwr.mm6913e2

Chen, J., & Subbarao, K. (2007). The immunobiology of SARS. Annual Review of Immunology, 25, 443-472. doi.org/10.1146/annurev.immunol.25.022106.141706

Dietz, W., & Santos-Burgoa, C. (2020). Obesity and its Implications for COVID-19 Mortality. Obesity. doi.org/10.1002/oby.22818

Fleming N. (2020). Coronavirus misinformation, and how scientists can help to fight it. Nature, 583(7814), 155–156. doi.org/10.1038/d41586-020-01834-3

Graham, J. W., Olchowski, A. E., & Gilreath, T. D. (2007). How many imputations are really needed? Some practical clarifications of multiple imputation theory. Prevention science, 8(3), 206-213. doi.org/10.1007/s11121-007-0070-9

Jin, J. M., Bai, P., He, W., Wu, F., Liu, X. F., Han, D. M., ... & Yang, J. K. (2020). Gender differences in patients with COVID-19: Focus on severity and mortality. Frontiers in Public Health, 8, 152. doi.org/10.3389/fpubh.2020.00152
King, G., Tomz, M., & Wittenberg, J. (2000). Making the most of statistical analyses: Improving interpretation and presentation. *American journal of political science*, 347-361. doi: 10.2307/2669316

Koçak, D. (2019). A Method to Increase the Power of Monte Carlo Method: Increasing the Number of Iteration. *Pedagogical Research*, 5(1), em0049. doi.org/10.29333/pr/6258

Krause, N. M., Freiling, I., Beets, B., & Brossard, D. (2020). Fact-checking as risk communication: the multi-layered risk of misinformation in times of COVID-19. *Journal of Risk Research*, 1-8. doi.org/10.1080/13669877.2020.1756385

Lachmann, A. (2020). Correcting under-reported COVID-19 case numbers. *medRxiv*.

Lai, C. C., Shih, T. P., Ko, W. C., Tang, H. J., & Hsueh, P. R. (2020). Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and corona virus disease-2019 (COVID-19): the epidemic and the challenges. *International journal of antimicrobial agents*, 105924. doi.org/10.1016/j.ijantimicag.2020.105924

Mansfield, E. R., & Helms, B. P. (1982). Detecting multicollinearity. *The American Statistician*, 36(3a), 158-160. doi.org/10.1080/00031305.1982.10482818
Mills, C. W., Johnson, G., Huang, T. T., Balk, D., & Wyka, K. (2020). Use of Small-Area Estimates to Describe County-Level Geographic Variation in Prevalence of Extreme Obesity Among US Adults. *JAMA Network Open*, 3(5), e204289-e204289. doi:10.1001/jamanetworkopen.2020.4289

Mooney, C. Z. (1997). *Monte carlo simulation* (Vol. 116). Sage publications.

O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & quantity, 41*(5), 673-690.

O'Connor, C., & Murphy, M. (2020). Going viral: doctors must tackle fake news in the covid-19 pandemic. *BMJ*, 24(369), m1587. doi: 10.1136/bmj.m1587

Ogen, Y. (2020). Assessing nitrogen dioxide (NO2) levels as a contributing factor to the coronavirus (COVID-19) fatality rate. *Science of The Total Environment*, 138605. doi.org/10.1016/j.scitotenv.2020.138605

Rajgor, D. D., Lee, M. H., Archuleta, S., Bagdasarian, N., & Quek, S. C. (2020). The many estimates of the COVID-19 case fatality rate. *The Lancet Infectious Diseases*. doi.org/10.1016/

S1473-3099(20)30244-9
Richardson, S., Hirsch, J. S., Narasimhan, M., Crawford, J. M., McGinn, T., Davidson, K. W., ... & Cookingham, J. (2020). Presenting Characteristics, Comorbidities, and Outcomes Among 5700 Patients Hospitalized With COVID-19 in the New York City Area. JAMA. doi:10.1001/jama.2020.6775

Saleh, M. (2020). The role of doctors in the COVID-19 “Infodemic.” Lean Forward Online, Harvard Medical School, May 19, 2020.

StataCorp. (2017). Stata Statistical Software: Release 15. College Station, TX: StataCorp LLC

Van Buuren, S. (2007). Multiple imputation of discrete and continuous data by fully conditional specification. Statistical methods in medical research, 16(3), 219-242. doi.org/10.1177/0962280206074463

Wang, W., Tang, J., & Wei, F. (2020). Updated understanding of the outbreak of 2019 novel coronavirus (2019-nCoV) in Wuhan, China. Journal of medical virology, 92(4), 441-447. doi.org/10.1002/jmv.25689

Wortham JM, Lee JT, Althomsons S, et al. Characteristics of Persons Who Died with COVID-19 — United States, February 12–May 18, 2020. MMWR. Morbidity and Mortality Weekly Report, 69. doi.org/10.15585/mmwr.mm6928e1

Wu, X., Nethery, R. C., Sabath, B. M., Braun, D., & Dominici, F. (2020). Exposure to air pollution and COVID-19 mortality in the United States. medRxiv. doi.org/10.1101/2020.04.05.20054502
Wu, Y. C., Chen, C. S., & Chan, Y. J. (2020). The outbreak of COVID-19: An overview. *Journal of the Chinese Medical Association, 83*(3), 217. doi: 10.1097/JCMA.0000000000000270

Yang, J. K., Feng, Y., Yuan, M. Y., Yuan, S. Y., Fu, H. J., Wu, B. Y., ... & Xu, X. (2006). Plasma glucose levels and diabetes are independent predictors for mortality and morbidity in patients with SARS. *Diabetic Medicine, 23*(6), 623-628. doi.org/10.1111/j.1464-5491.2006.01861.x

Zhou, F., Yu, T., Du, R., Fan, G., Liu, Y., Liu, Z., ... & Guan, L. (2020). Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study. *The Lancet*. doi.org/10.1016/S0140-6736(20)30566-3

Zhou, Y., Cowling, B. J., Wu, P., Chan, W. M., Lee, S. Y., Lau, E. H., & Schooling, C. M. (2015). Adiposity and influenza-associated respiratory mortality: a cohort study. *Clinical Infectious Diseases, 60*(10), e49-e57. doi.org/10.1093/cid/civ060
Table 1: Descriptive statistics

| Variable                             | Mean | SD  | Min  | Max  |
|--------------------------------------|------|-----|------|------|
| **Demographic/Economic**             |      |     |      |      |
| Age                                 | 71.00| 7.71| 60.00| 85.00|
| Male                                 | 44%  |     |      |      |
| Currently married                    | 45%  |     |      |      |
| Less than HS                         | 12%  | 33% |      |      |
| High school                          | 29%  | 46% |      |      |
| Some college                         | 29%  | 45% |      |      |
| College                              | 17%  | 37% |      |      |
| Advanced degree                      | 13%  | 33% |      |      |
| Family income <$35,000               | 43%  | 45% |      |      |
| Family income $35k–49,999            | 13%  | 36% |      |      |
| Family income $50k–74,999            | 17%  | 32% |      |      |
| Family income $75k–99,999            | 10%  | 28% |      |      |
| Family income $100,000+              | 17%  | 36% |      |      |
| **Health Insurance**                 |      |     |      |      |
| Insurance Type       | Percentage |
|---------------------|------------|
| Medicare            | 75%        |
| Medicaid            | 9%         |
| Private Insurance   | 54%        |

**Health Status**

| Health Condition       | Percentage |
|------------------------|------------|
| BMI                    | 27.92      |
|                        | 5.85       |
|                        | 11.67      |
|                        | 55.89      |
| Diabetes               | 24%        |
| Hypertension           | 60%        |
| Coronary heart disease | 13%        |

N = 34,881
Table 2: Odds ratios from logit regression for mortality

| Mortality          | At best       |                     |                        | At worst       |                     |                        |
|--------------------|---------------|---------------------|------------------------|---------------|---------------------|------------------------|
|                    | Odds Ratio    | Std. Err. | [95% Conf. Interval]  | Odds Ratio    | Std. Err. | [95% Conf. Interval] |
| *Demographic/Economic* |               |           |                        |               |           |                        |
| Age                | 1.22**        | 0.10      | 1.05                   | 1.42          | 1.27***   | 0.09                   | 1.11                   | 1.45                   |
| Male               | 1.02          | 0.05      | 0.92                   | 1.12          | 1.05      | 0.05                   | 0.96                   | 1.16                   |
| Currently married  | 1.03          | 0.05      | 0.94                   | 1.13          | 1.02      | 0.05                   | 0.93                   | 1.13                   |
| Less than HS       | 0.92          | 0.09      | 0.77                   | 1.11          | 0.89*     | 0.07                   | 0.77                   | 1.03                   |
| Some college       | 1.00          | 0.06      | 0.88                   | 1.12          | 1.00      | 0.05                   | 0.91                   | 1.10                   |
| College            | 1.00          | 0.09      | 0.83                   | 1.20          | 0.98      | 0.06                   | 0.86                   | 1.11                   |
| Advanced degree    | 0.94          | 0.07      | 0.80                   | 1.10          | 0.99      | 0.08                   | 0.84                   | 1.16                   |
| Total family income| 1.00          | 0.00      | 0.99                   | 1.01          | 1.00      | 0.00                   | 0.99                   | 1.01                   |
| *Health Insurance* |               |           |                        |               |           |                        |
| Medicare           | 1.10          | 0.09      | 0.95                   | 1.28          | 0.93      | 0.07                   | 0.81                   | 1.07                   |
| Medicaid           | 0.97          | 0.08      | 0.82                   | 1.14          | 1.08      | 0.10                   | 0.89                   | 1.30                   |
| Private Insurance  | 1.02          | 0.05      | 0.93                   | 1.11          | 1.04      | 0.05                   | 0.95                   | 1.14                   |
| *Health Status*    |               |           |                        |               |           |                        |
| Condition             | Estimate | Standard Error | CI Lower | CI Upper | p Value |
|-----------------------|----------|----------------|----------|----------|---------|
| BMI                   | 1.04***  | 0.00           | 1.02     | 1.04     | 0.00    | 1.02    | 1.03    | 
| Diabetes              | 1.19***  | 0.06           | 1.08     | 1.32     | 1.03    | 0.05    | 0.94    | 1.13    | 
| Hypertension          | 1.36***  | 0.14           | 1.09     | 1.66     | 1.17*** | 0.06    | 1.06    | 1.31    | 
| Coronary heart disease| 1.12*    | 0.07           | 0.99     | 1.27     | 1.11*   | 0.07    | 0.98    | 1.24    | 

N= 34,881

***p<0.01, **p<0.05, *p<0.10
Figure 1: Mortality probabilities for at best case for overall sample, obesity, and hypertension

Note: the hypertension line is slightly below the obesity line for the at best case.

Figure 2: Mortality probabilities for at worst case for overall sample, obesity, and hypertension
Figure 1

At best case

Mortality (probability)

Age (years)

Overall
Hypertension
Obesity
Figure 2

At worst case

Mortality (probability)

Age (years)

Overall
Hypertension
Obesity