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Age Variation in COVID-19 Treatment in Mexico: A Retrospective Cohort Study

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Abstract

The COVID-19 pandemic has caused unprecedented stress on health systems throughout the world and the immense number of people infected has created demands for health care resources so high that rationing of medical equipment, especially ventilators, is inevitable. Administrators and physicians may follow certain guidelines or objectives and prioritize one types of patients over the other. Using data from Mexico, I study how intubation decisions vary with respect to patients' age after controlling for mortality risks. Intubation rates vary widely among patients of different characteristics; I estimate the mortality risks of patients and identify the high-risk ones using Cox proportional hazards model and develop a heteroskedastic probit model to predict the probability of a high-risk patient receiving intubation. My estimated model suggests that old patients (aged 70–100) have uniformly lower chance of receiving intubation across all risk levels than other patients, where at a certain risk level, middle-aged patients (aged 40–69) can have as much as 43% higher chance of receiving intubation than old patients. On the other hand, there is relatively smaller variation between how younger (aged 18–39) and middle-aged patients are treated. The findings in this study could help administrators and physicians make more informed decision regarding triage of patients.

1 Introduction

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is a novel coronavirus originated initially in Wuhan, China in late 2019 and causes coronavirus disease 2019 (COVID-19). Since 2019, COVID-19 has spread and created outbreaks rapidly across the world. The first cases of COVID-19 infection in Mexico were reported in early 2020 (Secretary of Health, Mexico, 2021), and the number of cases increased rapidly afterwards. At the time of writing, over 7 million cases have been reported.

Undoubtedly, the COVID-19 pandemic has created immense pressure on health systems worldwide including Mexico (Phelan et al., 2020). As in other public health disasters, prioritization of patients and rationing of scarce medical resources become an important part of the responses to COVID-19. Medical staff will follow established ethical standards and allocate resources (such as intensive care unit beds and ventilators) to patients who are likely to "benefit most" (Emanuel et al., 2020; Leclerc et al., 2020). Crudely speaking, patients who will benefit most from treatment are those whose outcomes are most likely to be altered because of intervention. For example, a 90-year-old diabetic patient with heart disease is not likely to benefit because he or she would have died with or without treatment, similarly, a 20-year-old otherwise healthy (having no comorbidities) individual is also not likely to benefit because he or she would have survived COVID-19 by himself/herself. Apart from that, patients with comorbidities (e.g., chronic kidney disease, diabetes, heart condition, hypertension etc.), especially multiple comorbidities, are more vulnerable and have higher mortality risks (McGoogan, 2020; Grasselli et al., 2020; Kalyanaraman Marcello et al., 2020; Rosenthal et al., 2020) and hence are given higher level of care in terms of intubation, such as ICU admission and mechanical ventilation. That said, established algorithms for triage of patients could be at risk of creating biases in deciding which patients should be given priority (Obermeyer et al., 2019), thus, an assessment of how treatment decisions are made with respect to patients age and risk is warranted.

In the this study, I examine large-scale administrative health data of COVID-19 patients in Mexico from January 2020 to May 2021 to study how treatment decisions, in particular intubation decisions, vary with respect to the age of patients after controlling for mortality risks. My frame work starts with a model-free descriptive analysis of ratios of patients intubated across different age groups among a subset of "complex" patients who have multiple comorbidities and thus are at high risk of mortality. Comparing intubation rates against mortality risk, I find that higher mortality risk does not necessarily lead to higher ratio of patients intubated and that the intubation rates vary non-linearly with mortality risk.

I then turn to estimate the probability of a patient receiving intubation given demographic and comorbidity variables. The estimation starts with the use of Cox proportional hazards model to construct a "hazard score" of patients that summarize their mortality risk. Then I identify patients who are at high risk of mortality as an effort to control for mortality risk. Using heteroskedastic probit models, I estimate the probability of a given patient receiving intubation. Looking at subgroups of patients categorized by age, I find that older patients (aged 70 or higher) have uniformly lower chance of receiving intubation than other patients, holding risk constant. And the most high-risk young patients (aged 18–39) have lower chance of receiving intubation than middle-aged (aged 40–69) patients at the same level of risk. The findings of this paper may help administrators and doctors make more informed decisions regarding prioritization of patients.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 describes how COVID-19 patients in Mexico are treated within the timeframe where data is available. Section 4 presents the descriptive analysis of variation in treatment with respect to patient age. Section 5 assesses physician decisions using heteroskedastic probit models and discusses the subsequent findings. Section 6 considers policy implications and shortcomings of the methodology. Section 7 concludes.

2 Data

The dataset used in this study is publicly available from the Mexican General Directorate of Epidemiology (Secretary of Health, Mexico, 2021)[1] which contains cases associated with COVID-19 in the Mexican healthcare system. Please see Table 1 for the description of a selected set of most relevant variables. I analyze, retrospectively, the decision made by medical personnel to intubate patients with regard to their demographics and comorbidities. The Mexican healthcare administration collects information regarding origin, demography, comorbidities, and outcomes of patients who are suspected to have contracted viral respiratory disease.

I accessed the latest version of the data on June 27, 2021 and omit roughly $11,000$ observations with either incomplete or erroneous data (Table 2 reports the details of the steps carried

[1] Other studies that utilize this data include, for example, Bello-Chavolla et al. (2020b,a) and Martos-Benítez et al. (2021).

out and the corresponding number of observations dropped). The sample restrictions result in a cohort of $7,042,816$ cases with suspicion of viral respiratory disease from January 1, 2020 to May 31, 2021. Among them, $4,019,314$ were tested positive for COVID-19 (positive SARS-CoV-2 RT-PCR[2]), here after "COVID-19 patients", and the remaining patients are COVID-19 negative (there is no pending result). Most of the time the analysis focuses only on patients who are COVID-19 positive. Figure 1 depicts the flowchart of patients and Table 3 presents the descriptive characteristics of selected demographic, comorbiditiy and clinical outcome variables of COVID-19 patients. In particular, I am interested in how probability of receiving endotracheal intubation[3] varies with regard to the characteristics of patients. All analyses are carried out with R version 4.0.4 (R foundation for Statistical Computing; Vienna, Austria).

2.1 Characteristics and Outcomes of COVID-19 Patients

Among the $4,019,314$ patients who are tested positive for COVID-19, the mean age is 41.9 years (SD 17.3 years), and $408,203$ (10.9%) are more than 65 years old. Male and female patients account for 48.3% and 51.7% respectively. Intensive care unit (ICU) admission and endotracheal intubation are given to $51,877$ (1.29%) and $73,408$ (1.83%) of the patients respectively. Pneumonia is diagnosed in $452,331$ (11.25%) of the patients and overall mortality rate is 6.08% ($244,312$ patients). For patients who died, their median and mean time from medical contact to mortality are 6 and 8.63 days respectively.

2.2 Comorbidities of COVID-19 Patients

Although it is not entirely clear how the various comorbidities are related to COVID-19 (Martos-Benítez et al., 2021), studies have shown that chronic comorbidities are prevalent among COVID-19 patients and are associated with severe cases and adverse outcomes (de Lusignan et al., 2020; Onder et al., 2020; Yang et al., 2020). Among the patients who are COVID-19 positive, $1,274,168$ (31.7%) of them have at least one chronic comorbidity[4], $467,624$ (11.6%) have at least two, and $137,529$ (3.42%) have three or more. The top three most common comorbidities are hypertension ($627,689$; 15.62%), obesity ($536,585$; 13.35%), and diabetes ($466,875$; 11.62%). The average age of patients with chronic comorbidities is higher than that of patients

[2]Reverse transcription polymerase chain reaction – a laboratory technique for testing COVID-19.
[3]Hereafter used interchangeably with intubation, invasive ventilation, mechanical ventilation, etc.
[4]Here defined as any of the followings: asthma, cardiovascular disease, chronic kidney disease, chronic obstructive pulmonary disease (COPD), diabetes, hypertension, and obesity.

without chronic comorbidities (51.3 vs. 37.5 years; $p < .001$). Loosely speaking, the characteristics of patients in Mexico in terms of comorbidities are quite similar to those in the United States (see, for example, Richardson et al. (2020) and Petrilli et al. (2020)).

3 Treatment of COVID-19 Patients

Mechanical ventilation has been one of the main ways of treating critically ill and hypoxic patients during the COVID-19 pandemic and there have episodes of ventilators shortages around the world. Despite efforts to establish guidelines for allocation of critical medical resources during a pandemic (for example, White et al. (2009)), physicians in different countries vary greatly in expectations, clinical practices and hence decision making, in addition to already existing variation in availability of resources (Wunsch, 2020; Wunsch et al., 2008). Studies carried out in China, Italy, the United Kingdom, and the United States point to large variation in ratios of COVID-19 patients given mechanical ventilation, ranging from less than 3% to more than 30% of hospitalized patients (Guan et al., 2020; Grasselli et al., 2020; Goyal et al., 2020) and great variation in ratios of COVID-19 patients admitted into ICUs, ranging from 5% to more than 27% of hospitalized patients (Guan et al., 2020; Petrilli et al., 2020).

In the case of Mexico, 658,602 (16.39%) of the COVID-19 patients are hospitalized and among them, 51,877 (7.88%) have been admitted into ICUs and 73,408 (11.15%) have been intubated. Similar to other studies that find very high mortality rates for patients admitted into ICUs[5], the data in Mexico show that patients who are admitted into ICUs have an average mortality rate of 47.66% (24,725 of the patients ever admitted into ICUs died). However, partly because of severe shortage of ICU beds and ventilators in Mexico (Mexico News Daily, 2021a,b), many patients who died actually were never put into ICUs or intubated: among the 244,312 COVID-19 patients who died, 92.31% (225,530) were admitted into hospitals, but only 10.12% (24,725) and 22.74% (55,545) were ever admitted into ICUs or intubated respectively. In particular, the absence of critical care (either admission into ICU or intubation) for some of those patients who died did not happen because their condition deteriorated too quickly, in fact, the time elapsed between symptoms onset and medical contact/death of these patients is similar to that of those who did receive critical care. Table 4 presents several time-related statistics of five different groups of COVID-19 patients that are treated differently.

[5]For example, ICNARC (2021) in the UK finds that among the 26,550 patients admitted into ICUs (of whom 26,192 have outcome, either discharge or death, determined), 9,956 (37.5%) died.

Regarding factors that are associated with provision[6] of critical care for COVID-19 patients, several prominent ones include (old) age, male gender, obesity, heart disease, and diabetes (Petrilli et al., 2020). Patients who are more than 60-years-old have significantly higher mortality risk, and patients between ages 21 and 60 are relatively less likely to be admitted into hospitals and ICUs (relative to patients at or below age 20).

4 Descriptive Analysis

In this and the next section I look into how treatment decision varies with respect to patients' age and other demographics and comorbidities. In particular, I am interested in whether intubation decision exhibits variation with age *after controlling for mortality risk*. I have devised two approaches to study the problem, a descriptive approach that uses high-level summaries will be discussed in this section. And another quantitative approach combining survival analysis and probit models that return similar results will be discussed in the following section. The two approaches more or less independently establish the finding that the odds of receiving intubation (or ICU admission) does not increase linearly with age (and through age, mortality risk), but rather follows a "cubic" specification – one year in crease in age at a younger category leads to mediocre increase in odds of receiving critical care, but one year increase in age at middle ages leads to high increase in odds of critical care, and the same age increase at older ages lead to small or even decreasing odds of critical care – leading to a sideways "S" relationship between intubation and age or mortality risk.

4.1 Complex Patients

As part of the descriptive analysis in studying the relation between intubation and mortality risk, I identify a group of so-called "complex" patients (who are associated with higher risk of mortality) for two reasons: (i) to isolate and focus on patients who are the more ill and have higher chance of dying and thus are more likely to receive intubation, and (ii) to lessen the correlation between age and intubation (and mortality). For (ii), it is because in the entire cohort of COVID-19 patients, younger ones tend to be a lot healthier and if I were to carry out the analysis on the entire cohort, any true variation in treatment after controlling for risk

[6]Although it may seem semantical, it is important to bear in mind that during phases of shortage of critical care resources, there will be more patients who *need* critical care than patients who are *provided* critical care, and we can only observe the latter from the data.

would be obscured by the fact that younger patients tend to have a lot lower mortality risk. However, if I single out a subset of patients that are particularly ill, I can reduce the difference in mortality risk between younger and older patients and have hope of learning about variation in treatment given to patients of different ages that have comparable risk.

The approach to identifying COVID-19 patients that are at particularly high mortality risk involves carrying out multiple correspondence analysis (MCA) on all of the comorbidities available in the data[7] and select patients who suffer from multiple comorbidities. MCA is an extension of correspondence analysis that is applicable to a multiple categorical variables scenario (which is the case here as all the comorbidity variables are binary[8]) and can be viewed as a counterpart of principal component analysis (PCA) (Greenacre and Blasius, 2006). MCA takes the data points and projects them to a low-dimensional Euclidean space (for example two-dimensional which can be conveniently graphed) and by examining the proximity and distribution between variables we can identify those that tend to appear together (i.e., have high correlation) (Abdi and Valentin, 2007). MCA is particularly useful in helping to identify complex patients as it uncovers groupings of comorbidities and provides insights into relationships between comorbidities, which help me establish selection criteria for complex patients (Akturk et al., 2007). A two-dimensional plot of MCA result is provided in Figure 2 (Figure A1 provides additional MCA plots on COVID-19 patients who received intubation and patients who died.). Here I omitted any age-related variables in the MCA because my goal is to retain as much variation in age in the complex patients that I select, so I do not include age in the analysis.

By inspecting Figure 2 and Figure A1, I identify three clusters of comorbidities and hence define a set of "complex" patients as those that suffer from all three categories of comorbidities. More precisely, a patient is defined as complex if he or she has both of the categories of pre-existing chronic comorbidities (i. and ii.) and the category of derivative medical conditions (iii.):

i. Cardiovascular disease *or* chronic kidney disease *or* COPD,

ii. Diabetes *or* Hypertension *or* Obesity,

iii. Immunosuppression *or* other comorbidity *or* pneumonia.

There are $54,550$ such complex patients; in particular, the mortality rate of them is 43.95% ($23,976$ died); 85.71% ($46,753$), 12.55% ($6,844$) and 7.69% ($4,197$) are hospitalized, intubated

[7] Which are asthma, cardiovascular disease, chronic kidney disease, COPD, diabetes, hypertension, immunosuppression, obesity, pneumonia, and "other comorbidity" (literally means comorbidity other than the first eight).

[8] In other words, coded as 0 (No) or 1 (Yes).

and admitted into ICUs respectively. The characteristics of these complex patients, in comparison with COVID-19 positive and negative patients are summarized in Table 5. The treatments of the full cohort and only complex patients by age groups are also summarized in Table 6; it is worth noting that the variation in mortality risk is indeed relatively more homogenous across age groups among complex patients (though still increasing with age) than among the full cohort, also patients who are intubated are older on average and for patients 20 years or older, the majority of them (more than 70%) died without intubation. Figure 3 shows the age density plots regarding two clinical outcomes (intubation and death) of complex COVID-19 patients. As expected, all age densities appear to be left-skewed (because we selected relatively more ill patients), and patients who were intubated and/or died tend to be older than the whole cohort. Some patterns in treatment is noteworthy: (i) there is a "bulge" in cases who are around the age of 30 who are at considerable mortality risk[9] yet received relatively less intubation, (ii) share of patients who receive intubation tends to decline beyond the age of 80, despite increasing mortality risk, and (iii) the median age of intubation tends to be younger than that of patients who died but older than that of all patients, suggesting that some patients of highest mortality risk (very old patients) are given lower priorities.

4.2 Non-intubated Death Rate

In this section I identify a variable that could be used as a proxy for mortality risk, as our final goal is to study the intubation treatment while controlling for mortality risk. However, using the mortality risk[10] of a certain age itself is not ideal because some of the patients are intubated, to work around this issue, I consider the variable "non-intubated death rate" ($NIDR$) defined as *number of patients who are not intubated and died/total number of patients* at a particular age. Similarly, "intubation rate" (IR) is defined as *number of patients who are intubated/total number of patients* at a particular age. The following matrix summarizes the related ratios:

	Patient died	Patient survived
Intubated	Intubated and died (ID)	Intubated and survived (IS)
Not intubated	Not intubated and died (ND)	Not intubated and survived (NS)

$$\text{Non-intubated death rate } (NIDR) = \frac{ND}{ND + NS}$$

[9] The mortality risk for complex patients aged 30 to 39 is 27.76.%.

[10] Number of patients died/total number of patients.

$$\text{Death rate} = \frac{ID + ND}{ID + IS + ND + NS}$$

$$\text{Intubation rate } (IR) = \frac{ID + IS}{ID + IS + ND + NS}$$

Following the previous discussion, I take $NIDR$ is a proxy for death rate (or mortality risk) of all patients, whether intubated or not, and $NIDR$ involves only patients who are not intubated. This claim could be straightforward to readers who are aware of the fact that only a small portion of COVID-19 patients are intubated (making up only 1.83% and 12.55% of the entire cohort and of the complex patients respectively), so vast majority of patients are not intubated and $NIDR$ will naturally resemble death rate or mortality risk. Appendix A provides more discussion regarding the validity of this claim.

Then I proceed to explore how these ratios of interest vary across different age levels of patients. Figure 4 and Figure 5 display the relationship between IR and age among all COVID-19 patients and among complex COVID-19 patients respectively. Panel A of Figure 4 reveals that IR clearly follows a cubic relationship with respect to age and among older patients, it reaches local maximum at 77 years old. IR drops beyond 77 years of age probably because patients older than that age are sometimes deemed unlikely to benefit from intubation and thus are given lower priority (Emanuel et al., 2020; Leclerc et al., 2020), and/or because of preference of patients and their surrogates to not intubate (such as through singing a do-not-intubate order) (Wunsch, 2020). On the other hand, I would like to set a lower bound for the age range that I want to study; I use 18 years which is the threshold of adulthood in Mexico. I exclude patients who are younger than 18 years old because neonates require dedicated ventilators and children and adolescents may be treated in systems separate from those of adults (such as children hospitals). Panel B of Figure 4 displys the scatter plot of IRs with age range restricted to 18 to 100.

Then I put $NIDR$ and IR of complex COVID-19 patients together and estimate IR (which is a representation of clinical decision) using $NIDR$ (which is a proxy for mortality risk) by the following linear and quadratic equation,

$$IR_i = \alpha + \beta NIDR_i + \varepsilon_i, \tag{1}$$

$$IR_i = \gamma + \delta NIDR_i + \zeta NIDR_i^2 + \varepsilon_i. \tag{2}$$

Where $i \in \{19, \ldots, 96\}$ are the age levels used in the estimation after (i) restricting age range to between 18 and 100[11], and (ii) excluding age levels that have less than 50 observations. Figure 6 shows a scatter plot of IR versus $NIDR$ with Equation (2) fitted. And Table 7 presents the model estimates. Generalized maximally selected statistics are calculated to test the two sided, simple cutpoint, alternative against the null hypothesis of independence between $NIDR$ and response variable IR (Hothorn and Zeileis, 2008). The null hypothesis is rejected at 1% level[12], suggesting an estimated cutpoint at 23.08% of $NIDR$ which corresponds to age 32. Panel A of Figure 7 presents a replication of Figure 6 but estimating Equation (1) with two subgroups: (i) patients between age 18 and 32 (the `Young` group) and (ii) patients patients between age 33 and 96. The right-hand-side subgroup in the figure clearly suggest another possible cutpoint among older patients, hence I divide the patients first into two groups by median $NIDR$ and test them individually for cutpoints. The results suggest two cutpoints at $NIDR = 23.08\%$ (corresponding to age 32; $p < 0.0001$) and at $NIDR = 46.88\%$ (corresponding to age 72; $p < 0.001$). Panel B of Figure 7 shows the scatter plot of IR versus $NIDR$ with three subgroups by age.

Panel B of Figure 7 points to some variation in treatment of complex COVID-19 patients with respect to $NIDR$ (or age), as we see that IR increases modestly with respect to $NIDR$ at lower levels (corresponding to age 18 to 32, "young"), becomes higher and increases more rapidly at mid-levels (corresponding to age 33 to 72, "middle") and eventually falls at very high $NIDR$ which is equivalent to very high mortality risk (corresponding to age 73 to 96). The latter part of variation can be explained by deprioritization of severely ill and very old patients – guidelines regarding allocation of critical resources during public health disasters have been discussed and established suggesting withdrawal of ventilators from patients whose illnesses are too severe that they have minimal probability of benefiting from mechanical ventilation or surviving intensive care (Powell et al., 2008; Biddison et al., 2019; Piscitello et al., 2020). While the first part of the variation where younger but still high-risk patients see a downward shift in IR *relative to* $NIDR$ is not as intuitive and will be studied further in the next section.

[11] Patients older than 100 years old are excluded because there are too few observations and it is unclear whether the data give an accurate representation of patients beyond 100 years old as many might have died before they are tested positive for COVID-19 (this also explains why mortality rate is actually lower for those aged between 100 and 109 compared to 90 and 99 as only the very healthy patients get to live at least until they receive COVID-19 testing.). Please see Table 6 for distribution of ages of patients.

[12] The test statistic is 5.6014 with $p < 0.0001$.

5 Assessing Intubation Decisions

The result in the previous section points to possible variation in treatment given to younger, middle-aged and older patients with younger (but still high risk) patients being given not as much care than middle-aged patients relative to mortality risk. To assess how much care is given to the three groups of patients while controlling for mortality risk, we need to partition the patients by risk levels and compare within each segment to see if younger patients received less intubation; since we will be looking within groups that have the same risk level, an association between lower chance of receiving intubation and young age might be seen as age discrimination.

5.1 Survival Analysis for Estimating Mortality Risk

To classify patients by mortality risk (with each risk level containing as much variation in age as possible so that variation in treatment can be studied), I use similar approach as in Bello-Chavolla et al. (2020b) and establish a predictive score for COVID-19 mortality using a Cox proportional hazards regression model. To ensure validity of the score on the more recent data, I go through the construction and validation processes starting with a 80/20 random train-test split of the dataset stratified by mortality, using patients between 18 and 100 years old inclusive and excluding observations with missing data (training set: $n = 3,031,151$, deaths $= 191,423$; test set: $n = 757,787$, deaths $= 47,742$), then estimate the survival curves using the Kaplan-Meier method.

The score capturing mortality risk (or "hazard score") is essentially a weighted sum of risk factors ($1 =$ Yes and $0 =$ No) using as weights the coefficients of a Cox regression model, and it serves as an one-dimensional summary of health status. As one of the survival analysis methods, the model evaluates the association between survival time of patients and predictors (which are the demographic and comorbidity variables). Here we are interested in the (expected) duration of time until the occurrence of death calculated by date of accessing the data[13] or date of death minus date of symptoms onset (for patients known to have died)[14] The Cox model is expressed by a hazard function denoted by $\lambda(t)$ which could be seen as the risk of dying at time t, and it

[13]Which is June 27, 2021; the data cover patients up to May 30, 2021.

[14]Because the dataset does not state explicitly whether a patient has been discharged (recovered), it is possible that some recent patients have not recovered from COVID-19 and are still at risk of dying, hence the observations are "right-censored".

is estimated as follows (Cox, 1972):

$$\lambda(t) = \lambda_0(t) \times \exp\{\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p\}, \tag{3}$$

or equivalently

$$\ln\left[\frac{\lambda(t)}{\lambda_0(t)}\right] = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p, \tag{4}$$

where t represents survival time; $\lambda(t)$ is the hazard function determined by a vector of risk predictors $X = (X_1, X_2, \ldots, X_p)$; the coefficients $\beta = (\beta_1, \beta_2, \cdots, \beta_p)$ measure the impact of predictors; and the term λ_0 is the baseline hazard function with $X = 0$. Since there are a lot more observations than regressors, there should not be significant concern about overfitting. Note that I am using Age as a continuous variable in the regression instead of the usual approach of using categories (where easily interpretable hazard ratios can be produced), this is because I do not want to create jumps in the estimated mortality risk which will impede subsequent analysis (see Section 5.2). After estimating the Cox model, we can consider the hazard rate of each predictor where $\beta_j > 0$ means that the corresponding variable increases risk and vice versa.

Having determined the hazard rates (i.e., coefficients of Cox regression), we construct the hazard score of patient i:

$$S_i = X_i'\beta, \tag{5}$$

where X_i is a $p \times 1$ vector of predictors of patient i and β is a $p \times 1$ vector of coefficients (i.e., S_i is a dot product of coefficients and predictors). Then we have essentially carried out a dimension reduction process where we abstract from predictor information in p-dimension a one-dimensional measure of mortality risk. Then I stratify the patients into 5 categories by grouping neighboring hazard scores as "very low risk", "low risk", "moderate risk", "high risk" and "very high risk"[15]. Table 8 presents the Cox model estimates using individual predictors, hazard score and risk stratification categories, and we can see that the three models performed similarly well using data in the training set. The model is also validated using the 20% test set and it is observed that the hazard score retained its discriminative and predictive power (C-statistic = 0.918[16]), so as the risk categories (C-statistic = 0.906), suggesting that the

[15] The density plot of the hazard score and the four cutoffs chosen to stratify patients into five risk categories are presented in Figure A2.

[16] The C-statistic, or concordance statistic, which ranges from 0.5 to 1 is a goodness-of-fit measure (the higher the better) for survival models Harrell Jr et al. (1996); the C-statistic is calculated as $c =$

models perform well in fitting the data and that it is not overfitted. Also, Figure 8 shows the Kaplan-Meier survival curves for the training set and test set.

5.2 Variation in Treatment

The hazard score allows us to stratify and group patients by mortality risk which facilitates the analysis of variation in treatment by age levels while controlling for mortality risk. Knowing how IR changes non-linearly with respect to $NIDR$ or age groups and following the approach of Abaluck et al. (2020), I model how intubation decisions depend on age and other predictors using a heteroskedastic probit model:

$$T_i = \mathbf{1}\left\{\frac{1}{\sigma_i}\left(X_i'\beta + \varepsilon_i\right) > 0\right\}, \tag{6}$$

where T_i is a binary variable of clinical treatment (intubation), X_i is a $p \times 1$ vector of independent variables of patient i and β is a $p \times 1$ vector of coefficients. σ_i^2 is the variance (or "scale parameter") of the error term ε_i where $\sigma_i = \exp(Z_i'\gamma)$ with Z_i being a $q \times 1$ vector of independent variables that are usually, but not necessarily, related to the regressors in (6) (Harvey, 1976; Alvarez and Brehm, 1995). The heteroskedastic probit model relaxes the assumption of the standard probit regression model that the variance of the error term is constant. The probit specification allows us to find the probability of "success" (i.e., $T_i = 1$) by

$$P(T_i = 1|X_i, Z_i) = \pi_i = \Phi\left(\frac{X_i'\beta}{\exp(Z_i'\gamma)}\right), \tag{7}$$

where $\Phi(\cdot)$, used as the link function here, is the cumulative distribution function of a standard normal distribution; and this leads to the following log-likelihood function that resembles the

$\frac{\#\text{ concordant pairs}}{\#\text{ concordant pairs} + \#\text{ discordant pairs}} = \frac{\sum_{i \neq j} \mathbf{1}\{\eta_i < \eta_j\}\mathbf{1}\{T_i > T_j\}d_j}{\sum_{i \neq j} \mathbf{1}\{T_i > T_j\}d_j}$. In the context here, we are interested in the occurrence of the event death and let T_i be the time to death and d_i be the death indicator of patient i, then we consider every pair of patients i and j (with $i \neq j$ and (i) if both of them are not "censored" (meaning the event death has occurred), we say they are *concordant* when $T_i < T_j$ whenever $S_i > S_j$ (i.e., higher-risk patient die in shorter time) and *discordant* otherwise, (ii) if only j is censored, we say that they are *concordant* if $T_j > T_i$ *and* $S_i > S_j$ (i.e., we know i died in a shorter time and had higher risk), *discordant* if $T_j > T_i$ *and* $S_i < S_j$ (i.e., i had lower risk yet died in shorter time), and ignore the pair if $T_j < T_i$ (because we cannot determine who would die in a shorter time), and (iii) if both patients are censored, we ignore the pair. The idea of C-statistic is analogous to the "accuracy" measure used in machine learning literature; it is defined as accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$, ($T = \text{True}, F = \text{False}, P = \text{Positive}, N = \text{Negative}$), also equivalent to the area under a receiver operating characteristic (ROC) curve.

one of a standard probit model:

$$\log L(\beta,\gamma|X_i,Z_i)=\sum_i\left\{T_i\log\Phi\left(\frac{X_i'\beta}{\exp(Z_i'\gamma)}\right)+(1-T_i)\log\left[1-\Phi\left(\frac{X_i'\beta}{\exp(Z_i'\gamma)}\right)\right]\right\}. \tag{8}$$

Specifically, I model probability of intubation as a function of age and other demographic and comorbidity variables as covariates. The first model is a baseline model that I estimate to predict intubation:

$$T_i=\mathbf{1}\left\{\frac{1}{\exp(Z_i'\gamma)}\left(\beta_1\text{Age}_i*\text{Young}_i+\beta_2\text{Age}_i*\text{Old}_i+Z_i'\delta+\varepsilon_i\right)\right\} \tag{9}$$

where T_i is an indicator for whether the patient is intubated; Young and Old are indicators for below 40 years old and above 70 years old, these two age levels are chosen based on the knowledge of variation in intubation rates across age levels found in Section 4. In other words, the middle-aged patients (aged 40–69) are used as reference to compare with patients who are young (aged 18–39) or old (aged 70–100). Z_i is a vector of demographic and comorbidity variables. Then, to capture the variation in probability of intubation with respect to age, I estimate another model that involves interaction between hazard score and age:

$$T_i=\mathbf{1}\left\{\frac{1}{\exp(Z_i'\gamma)}\left(\beta_1\text{S}_i\times\text{Young}_i+\beta_2\text{S}_i\times\text{Old}_i+\varepsilon_i\right)\right\} \tag{10}$$

where S_i is the hazard score of the patient hence mortality risk is controlled for. And the latent scale factor is again the covariates that were used to construct the hazard score. A second model that I estimate involves a squared age term while controlling for S_i:

$$T_i=\mathbf{1}\left\{\frac{1}{\exp(Z_i'\gamma)}\left(\beta_1\text{Age}_i+\beta_2\text{Age}_i^2+\beta_3 S_i+\varepsilon_i\right)\right\} \tag{11}$$

where the only difference between (11) and (10) lies in the variables of interest. The primary sample of patients used in analysis are those who are classified as "high risk" or "very high risk" among all COVID-19 patients[17] in Section 5.1 (i.e., the two highest risk categories)[18] ($n = 558,386$). My target is to identify the marginal effects of increase in hazard score on probability of receiving intubation at different age categories – young, middle, and old. The

[17] The model in Section 5.1 is trained again with the full COVID-19 cohort to uncover the risk categories.

[18] These two categories are used together because the "very high risk" category has too little variation in age – there are simply too few young patients (6 out of 189,124 are younger than 40 years old) for comparison and estimating a model on this sample will likely lead to large error. The same applies to lower risk categories which consist of mostly young patients.

basic characteristics and clinical outcomes of the five categories of patients are presented in Table 9, and the average intubation rates and mortality rates versus average hazard scores scatter plots across age levels are displayed in Figure 9. Figure A7a shows variation in treatment among this subset of patients who are chosen such that they are at more or less homogeneous mortality risk: (i) for young patients (aged between 18 and 39), their average intubation rates are somewhat stable despite variation in average hazard scores and increment in mortality rates, (ii) for middle-aged patients (aged between 40 and 69), their average intubation rates increase with respect to average hazard scores – at this age range, more risky patients receive more intubation, and (iii) for older patients (aged 70–100), for similar average mortality risks/hazard scores, they receive much less intubation relative to the other two groups, and higher risks actually lead to less intubation; in particular, it should be noted that despite the old age, my model suggests that this particular set of patients are not at significantly higher risk than the two younger groups (because of similar hazard scores), so the argument that these 70–100 years old patients are less likely to benefit from intubation will not hold. Still, older patients may be given lower priority for reasons other than lower likelihood of benefiting from critical care, for example, older patients have fewer years of life remaining and thus are less cost-effective to save as for the same usage of resources, more quality-adjusted life-years may be recovered (Emanuel et al., 2020; Briggs et al., 2021).

5.3 Results and Interpretation

The heteroskedastic probit estimates for intubation decision and mortality, among high-risk patients ($n = 372,464$) are presented in Table 10. The significance and negativity of the squared age term (as in Equation (11)) suggests that both intubation and mortality rates do vary non-linearly with respect to age. Column (2) of Table 10 points to evidence suggesting that relative to middle-aged patients (between 40 and 69), younger patients (age < 40) have greater increase in *z-score*[19] per unit increase in hazard score, while older patients (age ≥ 70) have much smaller increase in z-score per unit increase in hazard score, ceteris paribus. Note that using solely the coefficients estimated for a probit model, we are unable to tell how the probability of intubation changes per unit increase in hazard score because such change in probability also depends on the starting value of z-score which takes both the model estimates ($X_i'\beta$, in the numerator) and latent scale model estimates ($\exp(Z_i'\gamma)$, in the denominator). We

[19]See Equation (7), and note that the z-score also depends on the scale factor Z_i.

are also unable to tell explicitly how probability of intubation varies with respect to each year of age because age is only included in the regression as categories. On the other hand, column (3) of Table 10 suggests an inverted U-shape relationship between probability of intubation and age with middle-aged patients having higher chance of receiving intubation, after controlling for mortality risk (hazard score).

Since interpretation of the model coefficients (which translate into z-scores) is not too informative, we may turn to examine the *fitted probabilities* of intubation. Figure 10 shows the true average intubation rates and fitted median intubation probabilities by Equation (9) through (11) (corresponding to models 1 through 3) and we can see that the three models predict the true intubation rates fairly well, where we already know that, by examining the Akaike information criterion, model 1 fits the data most closely. Then we proceed to study the effects that age categories have on fitted probabilities of intubation.

Figure 11 shows the fitted probabilities against hazard scores by age groups using probabilities fitted with Equation (9). Judging from the fitted probabilities, two observations can be made: (i) older patients aged between 70 and 100 have relatively much lower chance of receiving intubation relative to both young and middle-age groups, and the probability actually decreases slightly as mortality risk increases for causes other than pneumonia; considering old patients who are at higher risks, if they were treated like middle-aged ones, the probability of receiving intubation could increase by as much as 43% (at hazard score 6.9). And (ii) young (aged 20–39) and middle-aged patients (aged 40–69) have similar probabilities of receiving intubation, and that the probability of receiving intubation increases with mortality risk, with middle-aged patients having steeper increase; considering the young patients that are at the highest risks, middle-aged patients at most have 24% higher chance of receiving intubation than them (at around hazard score 5.3). These results agree with findings in Section 4.2 and Figure 9.

That said, it also should be noted that by the construction of the hazard score, that age goes into it with a positive coefficient, for a given hazard score, the older the patient, the fewer comorbidities he or she will have (because the hazard score has to be compensated by having fewer comorbidities), and by the same token, the very young patients within this risk level tends to have many comorbidities. This is also reflected by the fact that patients' fitted average probabilities of intubation are separated by, in addition to age, whether the patients have pneumonia. And although Cox regression predicts that patients within this category are of similar risk, it is unclear how their risks are *perceived* by medical personnel, hence the separation in fitted intubation probability might be exaggerated.

5.4 Robustness

The findings presented above suggest some differential treatments given to patients in different age groups where (i) older patients face much less chance of receiving intubation and (ii) middle-aged patients receive higher increase in probability of intubation than younger patients per unit increase in hazard score (i.e., mortality risk). However, I acknowledge that the way young and middle-aged patients' probabilities separate as presented in Figure 11 is somewhat self-fulfilling – although Equation (9) does fit the data better than the other two models (in terms of having lower Akaike information criterion), it explicitly includes young and old categories which will inevitably cause the fitted probabilities to separate themselves. Hence I also study the probability values fitted by the other two specifications (Equations (10) and (11)). The scatter plots are shown in Figure A4, and indeed, we see that the difference in treatment between middle-aged and young patients becomes less apparent and there is little separation between these patients. That said, the other finding where older patients receive much less intubation after controlling for mortality risk is relatively more robust as probabilities fitted by all three models suggest that older patients' chance of receiving intubation is much lower.

To relate back to Section 4.2 where a subset of "complex" patients ($n = 53,636$) are identified and analyzed, as a robustness check I apply the analysis from Section 5.2 on complex patients as well. The result is shown in Figure A5 where we can see that the result aligns with those in Section 4.2 and Section 5.2 as the same tread where middle-aged patients receive relatively more intubation at a given hazard score can be seen, and that old (aged 70–100) patients' chance of receiving intubation decreases with mortality risk.

As another robustness/sensitivity check, I repeated the analysis in Section 5.2 and analyze all patients having hazard scores higher than 3 (roughly equivalent to studying also the "moderate" risk category), covering the top 24.2% highest-risk patients ($n = 918,744$). The model as in Equation (9) will be implemented again and the probabilities fitted again using this larger subset of patients. The resulting scatter plot is presented in Figure A6. Where we can see that the result is pretty much unchanged with the inclusion of moderate-risk patients (mostly young and pneumonia negative patients), suggesting that the findings are largely not sensitive to the choice of hazard score cutoff and the subset of patients studied.

5.5 Counterfactuals

Since the Mexican data include patients who are suspected of viral respiratory disease but *not* COVID-19 positive, I could look into patients who are COVID-19 negative and verify that the results presented in the preceding sections are unique to patients who are COVID-19 positive. There are $3,012,028$ cases of COVID-19 negative patients (among whom $2,823,478$ are complete) and I would apply the analysis presented in Section 5.2 on these patients. Table A1 presents the characteristics of COVID-19 negative patients, and as expected, they are healthier (in terms of having fewer comorbidities) than COVID-19 positive patients and have much more positive clinical outcomes.

Figure A7 depicts a summary of clinical outcomes (intubation and mortality) of COVID-19 negative patients. It can readily be noted that (by comparing with Figure 9) unlike COVID-19 positive patients, old COVID-19 negative patients do not receive less intubation as their mortality risk increases and old COVID-19 negative patients have similar mortality rates as middle-aged and young counterparts who are identified as high or very high risk via Cox regression model. As in the preceding section with a heteroskedastic probit model, I recover the fitted average probabilities of intubation for COVID-19 negative patients and the result is presented in Figure A8. We can immediately notice two major differences compared to the COVID-19 positive case: (i) young (aged 18–39) and middle-aged (40-69) patients follow essentially identical trend in terms of probabilities of receiving intubation, and (ii) despite having lower chance of receiving intubation at a given level of mortality risk (i.e., hazard score), old (aged 70–100) patients' chance of being intubated does increase with the hazard score, this is distinctively different from the COVID-19 positive case.

We may also be interested in exploring further how treatment varies for old and middled-aged patients, as discussed towards the end of Section 5.2 that for several reasons older patients may be given lower priority when allocating medical resources, hence it is to some degree expected to see old patients having lower chance of receiving intubation than middle-aged patients and that as seen from Figure A8, if old patients were treated as middle-aged patients, their chance of receiving intubation could increase by at most about 37.7% (at hazard score 8). Still, since there is virtually no difference in the ventilators needed by COVID-19 negative and positive patients, it means that COVID-19 negative patients still have to "compete" for resources and we can expect that widespread pandemic and shortages of ventilators have adversely affected their odds of receiving intubation. Hence it is unclear how much the gap between old and middle-aged patients during a period of pandemic reflects the situation during normal days. Nonetheless, if we assume that the gap in treatment is what would happen without the pandemic, we may see that old patients with COVID-19 are more negatively affected by shortages of resources both because their chance of receiving intubation drops with respect to mortality risk and there exists a larger gap between the treatment they receive and middle-age patients receive when compared with COVID-19 negative patients.

6 Discussion

6.1 Limitations

One major limitation of the study is that the administrative data are lacking in precision – most of the demographic and comorbidity variables are coded as binary leading to only a crude assessment of the health status of patients as little can be accurately known about how severe certain condition is. Or even worse, the data may not accurately reflect the status quo of the COVID-19 pandemic in Mexico due to the issues of under-reporting where many COVID-19 positive patients could have been omitted from this data for various reasons such insufficient testing (Rahmandad et al., 2020; Compare, n.d.). In general the lack of precision hampers the accuracy of the models implemented in this study as patients who appear to be similar in the data could actually vary in terms of severity and health status. The lack of precision also limits the approaches that can be used to study the data. For example, if vital signs or other more precise information of patients are available, then I could test the conditions required by a "judge leniency" design (for example, Kling (2006) and Chan Jr et al. (2019)) such as monotonicity and potentially use variation in how often physicians in different states of Mexico intubate patients (i.e., variation in "leniency"; which may be caused by varying availability of resources) to estimate how probability of mortality changes given different treatment using the 32 Mexican states as "judges" because patients could be seen as quasi-randomly "assigned" to receive treatment in various states.

Another limitation of the study is that, since the decision to provide critical care including intubation is highly selective, only patients who are deemed most in need are provided treatment (this is indirectly suggested by the fact that patients who received intubation have significantly higher mortality rates than those who do not, see Figure A9b). And the data only crudely classify patients because comorbidity variables are only binary, making it difficult to accurately gauge patient's health status because two patients having the same comorbidity could vary greatly in severity. Identification of patients who have the same health status and yet are given different treatment by chance could be made easier if more more sophisticated data like vital signs are available. Without knowledge of possible randomization of critical care among patients[20], I could not reliably study the potential treatment effect of intubation and other critical care intervention among different patients and how likely a patient is going to benefit. If randomized controlled trials were implemented among COVID-19 patients (under ethical conditions), then a causal forest model[21] can be used to estimate treatment effect of intubation (i.e., how will mortality risk be changed) on patients. A pandemic as widespread as the COVID-19 actually provides a rare opportunity where randomization of resources could be justified, as randomizing not treating some patients when there is no shortage of resources can hardly be ethical. Such valuable information regarding treatment effect will certainly help improve any allocation strategy currently adopted and help increase the number of lives or life-years that can be saved.

6.2 Policy Implication

In Section 5 I found some variation in treatment given to COVID-19 patients of different age groups after controlling for mortality risk. One more robust result is that older patients who are at the same mortality risk as younger and middled-age patients are given less intubation relative to the latter two groups, although this could be explained by the preference to save patients who are at earlier stages of life, so that all individuals are given equal opportunity to pass through different stages of life, from childhood, to old age (Williams, 1997); or that the goal may be to save as many life-years as possible (White and Lo, 2020). Administrators may assess whether the allocation of resources is appropriate by comparing how the likelihood of receiving intubation of patients in different age groups vary against the number of quality-adjusted life-years lost. Should the administrators have any public policy related goals to achieve, they can do so by manipulating the likelihoods of treatment between patients of different ages or other characteristics. Administrators and doctors may also want to establish an algorithm for predicting mortality risks of patients and the probabilities that they will benefit from critical

[20]Note that under very specific circumstances, when two patients have same prognosis and equal chance of benefiting from care, randomly allocating critical care resources could be ethical and also efficient (Persad et al., 2009).

[21]For example, Wager and Athey (2018) and Abaluck et al. (2020).

care so that treatment decisions can be aided (for example An et al. (2020)).

7 Conclusion

In this paper, I review the characteristics of and treatment received by COVID-19 patients in Mexico. I show the common comorbidities of patients in Mexico and find some prominent risk factors to be old age, chronic kidney disease, obesity, etc. I also construct a hazard score to summarize and predict patients' mortality risk using survival analysis including a Cox regression model. I then analyze the probability of receiving intubation using heteroskedastic probit model by three different age groups (young, middle, old) and find that older patients (above 70 years old) have uniformly lower chance of receiving intubation at given risk levels, and if they are treated as middle-aged patients, their chance of receiving intubation at most can increase by 43%. Younger (below 40 years old) and middled-aged patients (aged between 40 and 70) have more or less similar chances of receiving intubation, with middle-aged patients having slightly steeper increase in probability per unit increase in mortality risk.

Despite some limitations of the study such as having mostly categorical data and potential under-reporting of COVID-19 cases, I help recognize how probability of receiving medical treatment varies across patients of different age and mortality risk so that administrators and physicians could, combining with other information such as estimated number of life-year losses associated with deaths, make more informed decisions regarding triage of patients during a public health disaster. Regarding potential future research, studies could be carried out to estimate treatment effect of intensive care on patients of different ages using randomized controlled trials or judges leniency design.

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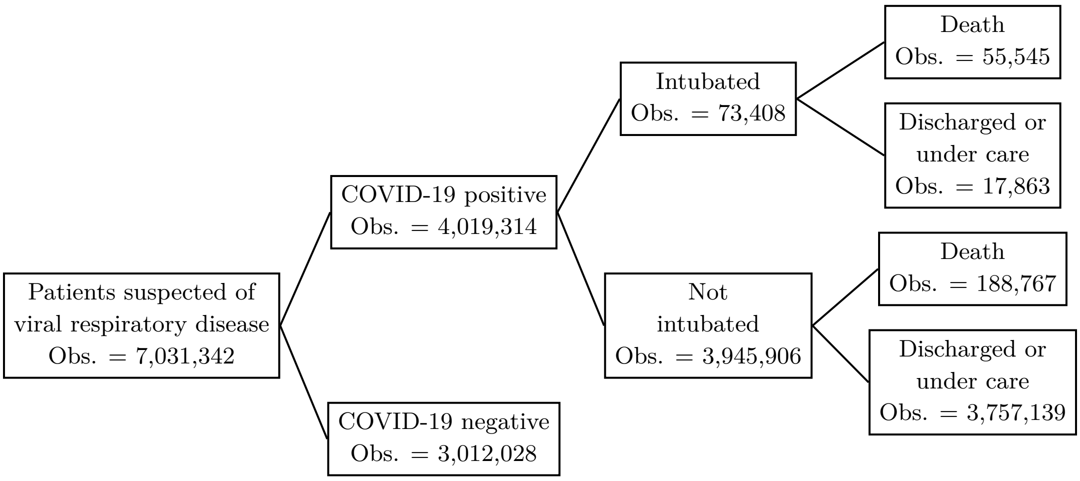
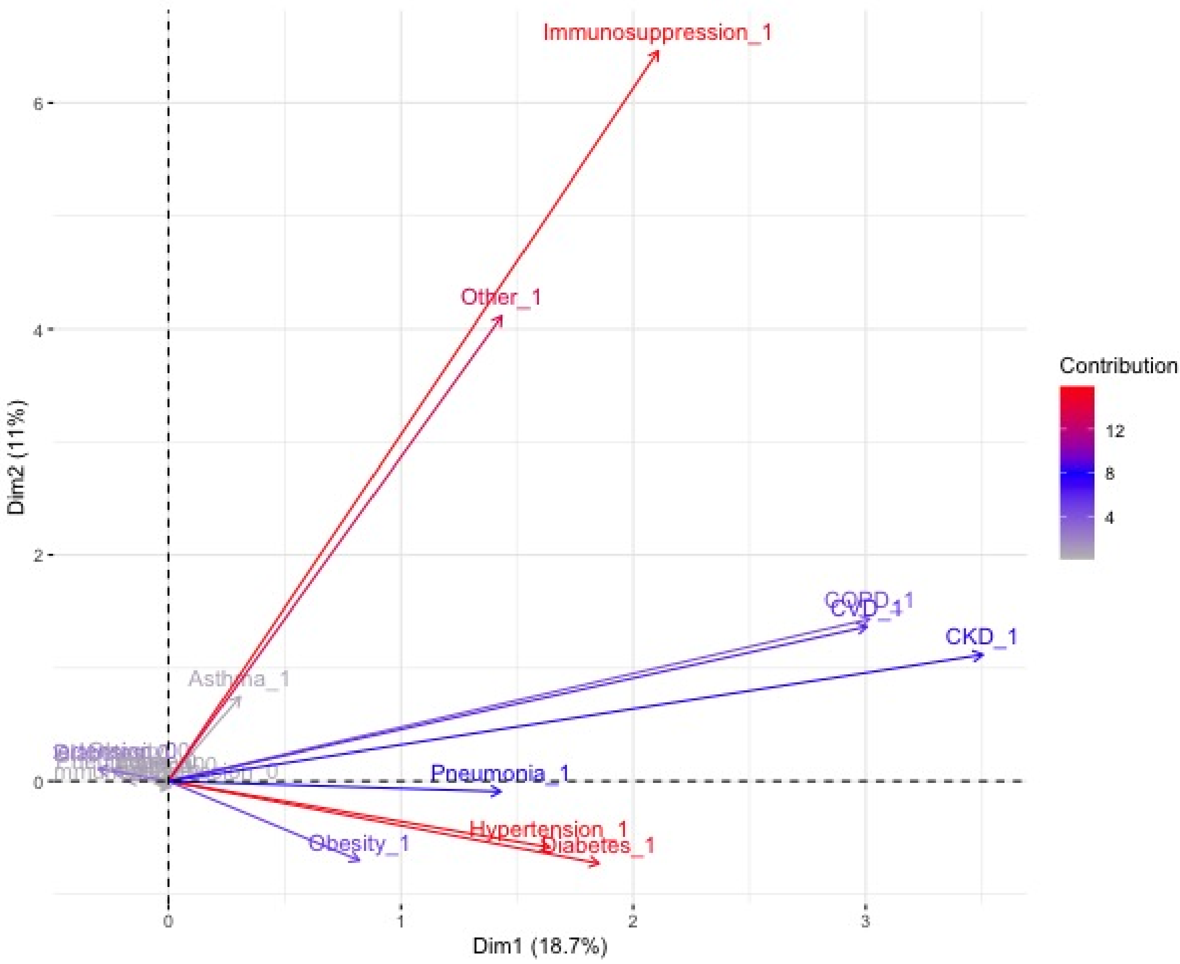
Figure 1: Flowchart of Patients



Note: This figure displays flowchart of observations after sample selection as described in Table 2.

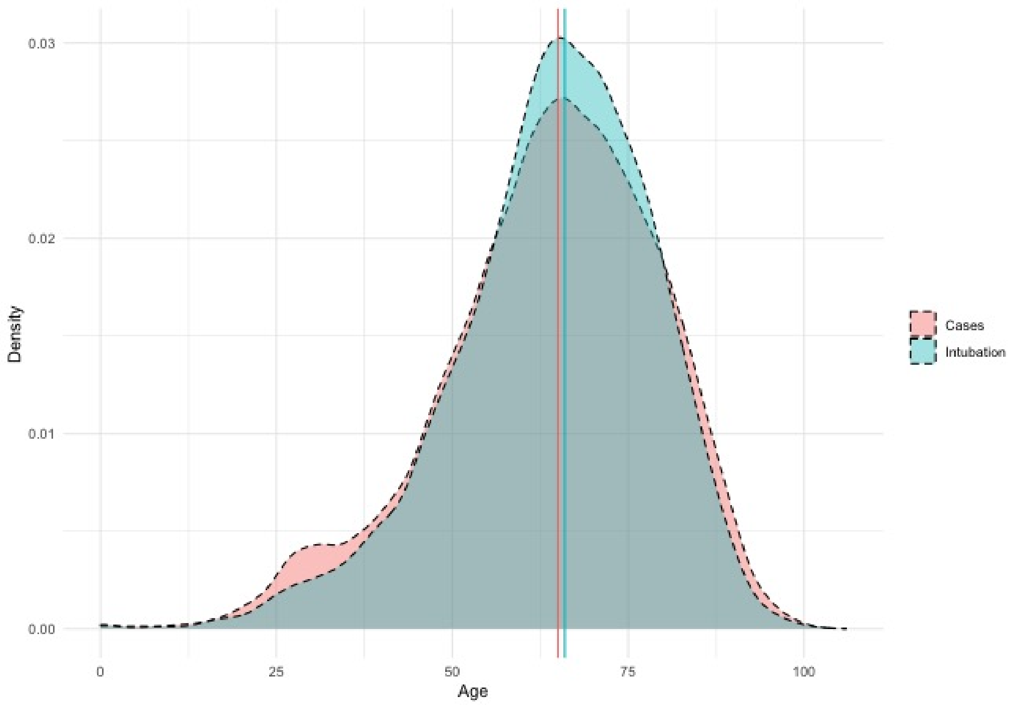
Figure 2: Multiple Correspondence Analysis (MCA) of Comorbidities of All COVID-19 Patients



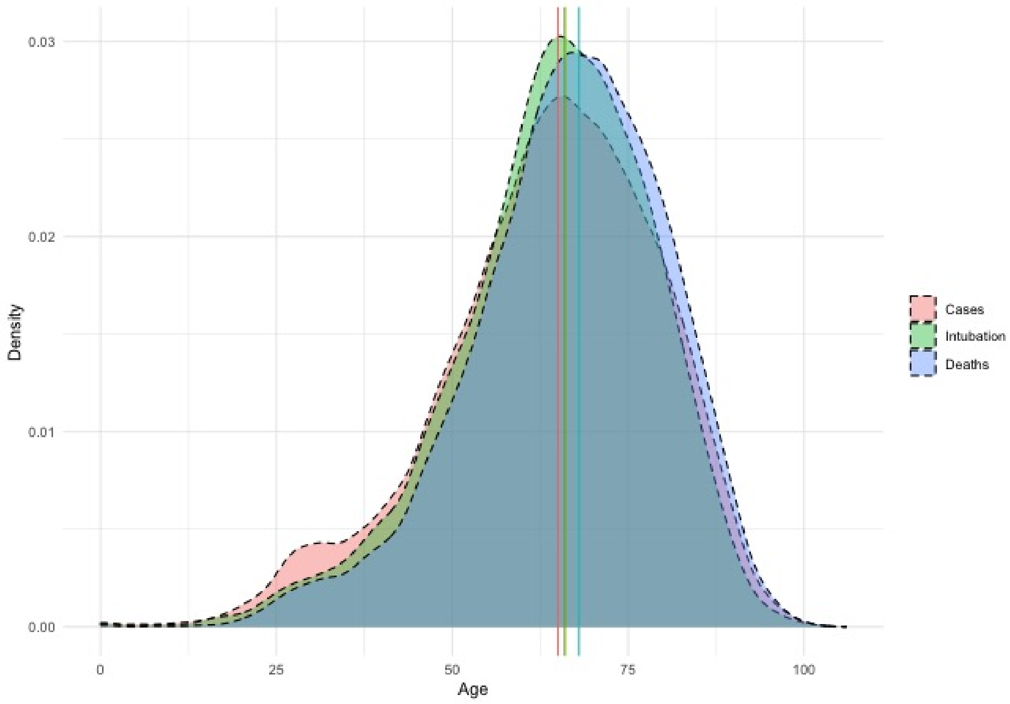
Notes: This figure displays a two-dimensional variables plot of the result of a MCA implemented on 9 comorbidities of all COVID-19 patients, excluding missing data ($n = 3,995,043$). The 9 comorbidities are asthma, cardiovascular disease (CVD), chronic kidney disease (CKD), chronic obstructive pulmonary disease (COPD), diabetes, hypertension, immunosuppression, obesity and other comorbidity (other). 1 = Yes and 0 = No.

Figure 3: Density Plots

(a) Age Distribution of Cases and Intubation of Complex COVID-19 Patients



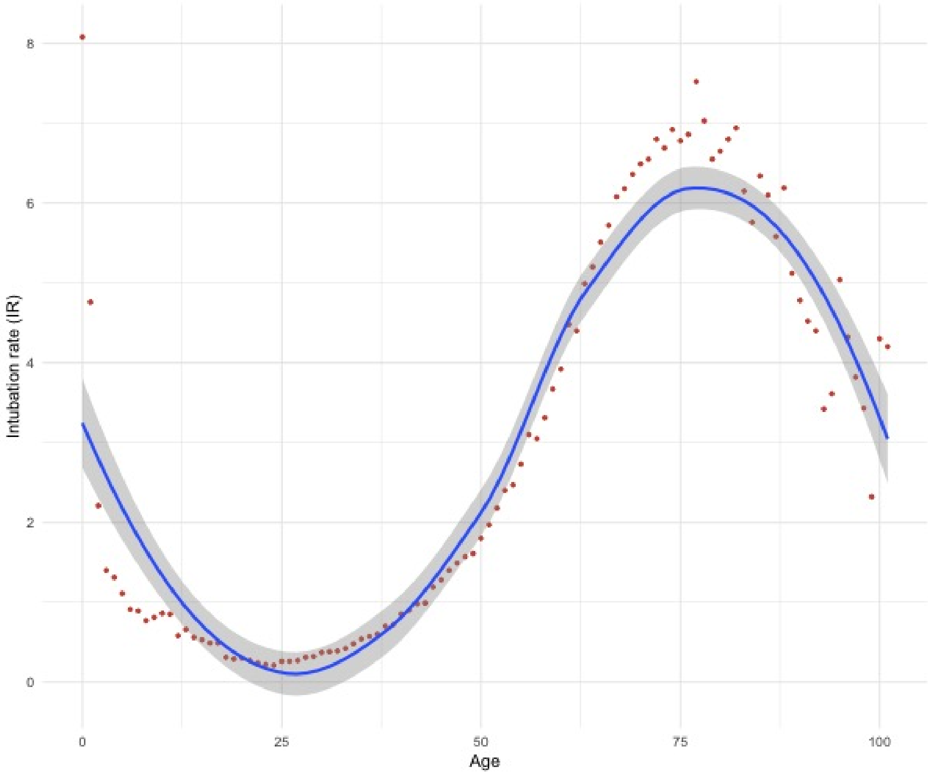
(b) Age Distribution of Cases, Intubation and Deaths of Complex COVID-19 Patients



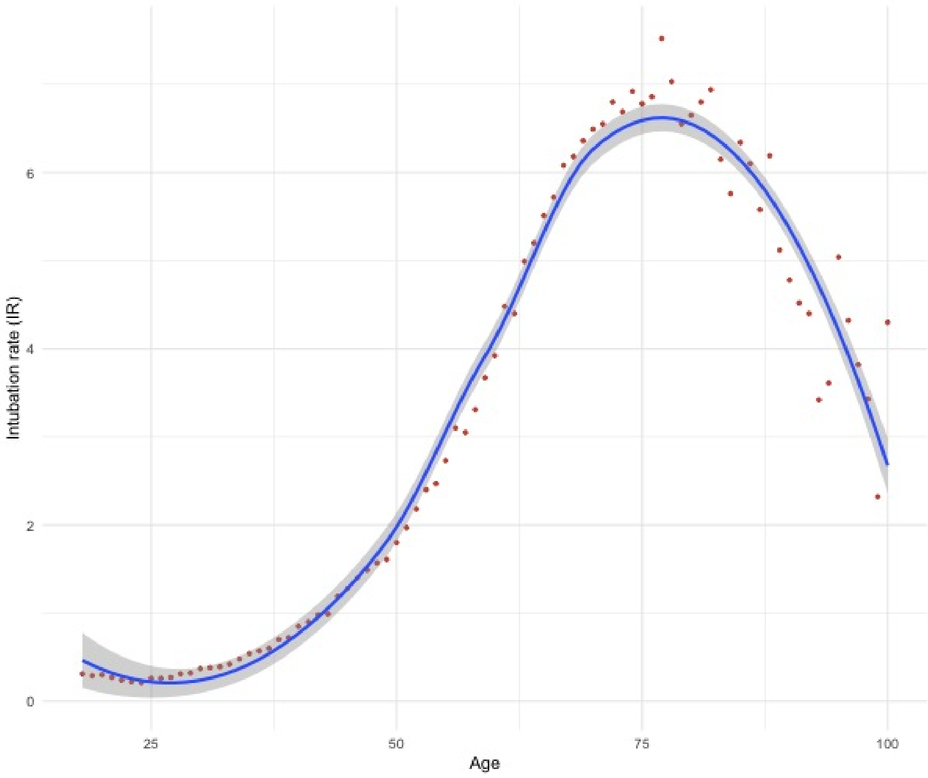
Notes: This figure displays the age density plots of all complex COVID-19 patients ($n = 54,550$) (`Cases`), intubated complex COVID-19 patients (`Intubation`) and complex COVID-19 patients who died (`Deaths`). Panel A displays the first two densities, and Panel B adds the third density to the two. The vertical lines indicate the medians of the ages of each corresponding group; the age medians (IQRs) are 65 (55–75), 66 (56–74) and 68 (58–76) for `Cases`, `Intubation`, and `Deaths` respectively. Abbreviation: *IQR*, interquartile range.

Figure 4: Scatter Plots

(a) Intubation Rates (IRs) Across Different Age Levels – All COVID-19 Patients

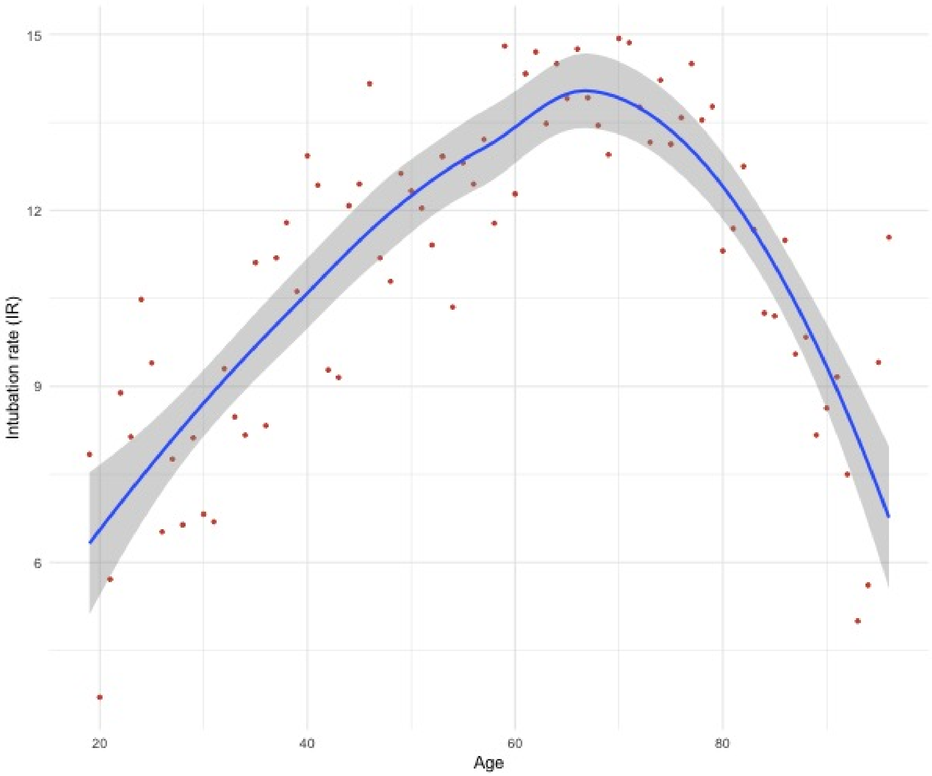


(b) Intubation Rates (IRs) Across Different Age Levels – All COVID-19 Patients Aged Between 18 and 90



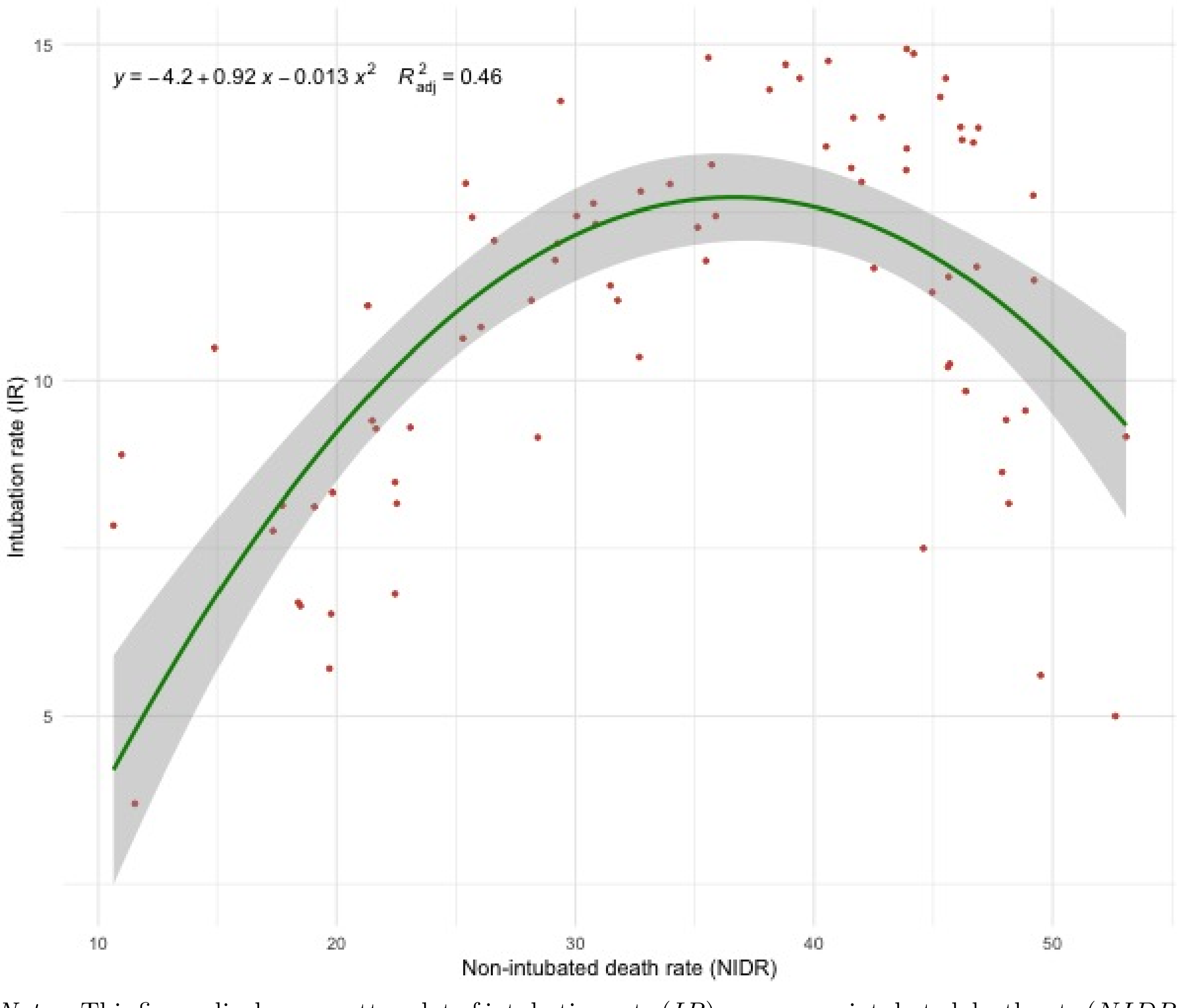
Notes: This figure displays the intubation rates (calculated as *number of patients intubated / number of patients*) across different age levels of all COVID-19 patients ($n = 4,019,314$), excluding levels that have less than 100 observations (resulting age range is 0–101), and fitted with locally estimated scatterplot smoothing curves (LOESS). Panel A shows the result for all ages and Panel B shows the result for ages further restricted to between 18 and 100 inclusive. Note that IR reaches a local maximum at 77.

Figure 5: Intubation Rates (IRs) Across Different Age Levels – Complex COVID-19 Patients Between Ages 18 and 90



Notes: This figure displays the intubation rates (calculated as *number of patients intubated / number of patients*) across different age levels of *complex* COVID-19 patients ($n = 54,550$), excluding levels that have fewer than 50 observations (resulting age rage is 19–96), and fitted with locally estimated scatterplot smoothing (LOESS) curves.

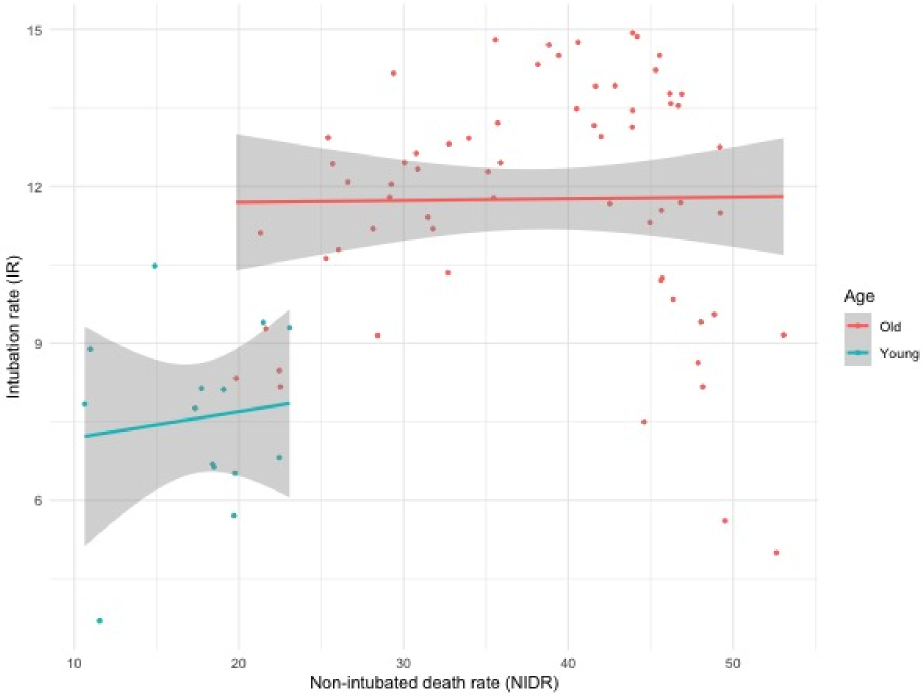
Figure 6: Intubation Rate Versus Non-intubated Death Rate



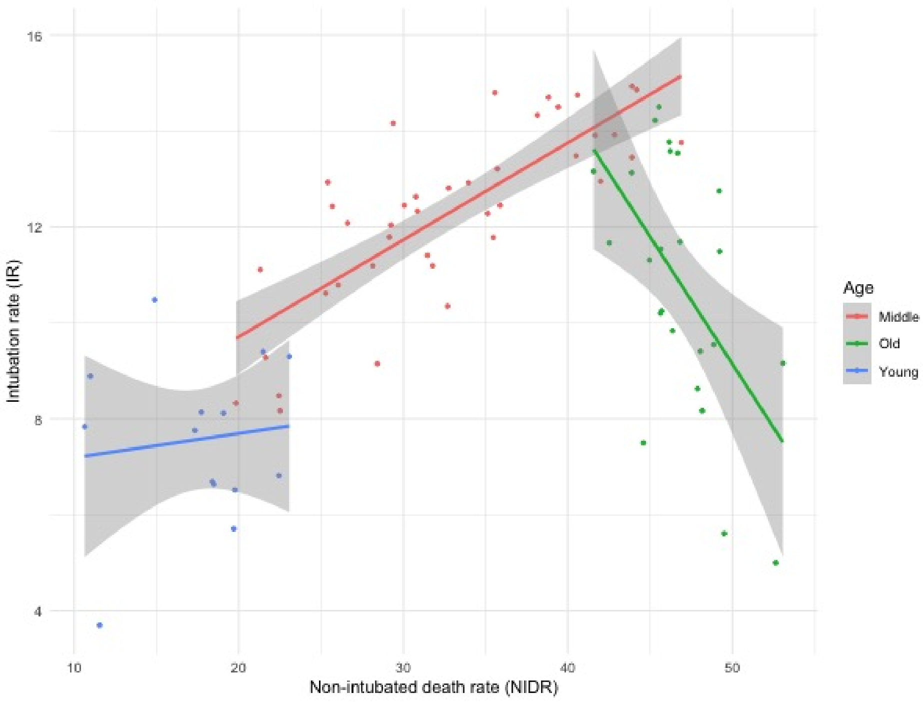
Notes: This figure displays a scatter plot of intubation rate (IR) versus non-intubated death rate ($NIDR$) of complex COVID-19 patients across ages 19 and 96 after excluding age levels that have fewer than 50 observations. A quadratic model $IR_i = \gamma_i + \delta_i NIDR_i + \zeta_i NIDR_i^2 + \varepsilon_i$ is estimated with the corresponding best-fit curve plotted in green and the equation displayed.

Figure 7: Intubation Rate Versus Non-intubated Death Rate

(a) Complex COVID-19 Patients Between Ages 19 and 90



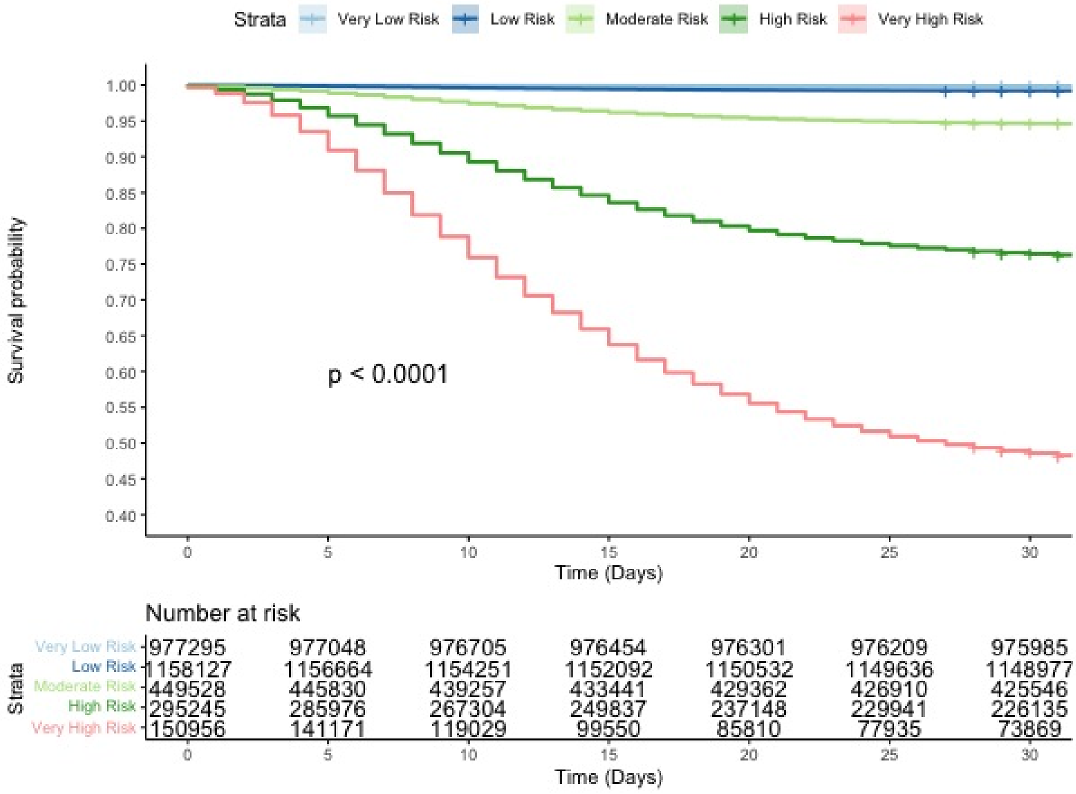
(b) Complex COVID-19 Patients Between Ages 19 and 80



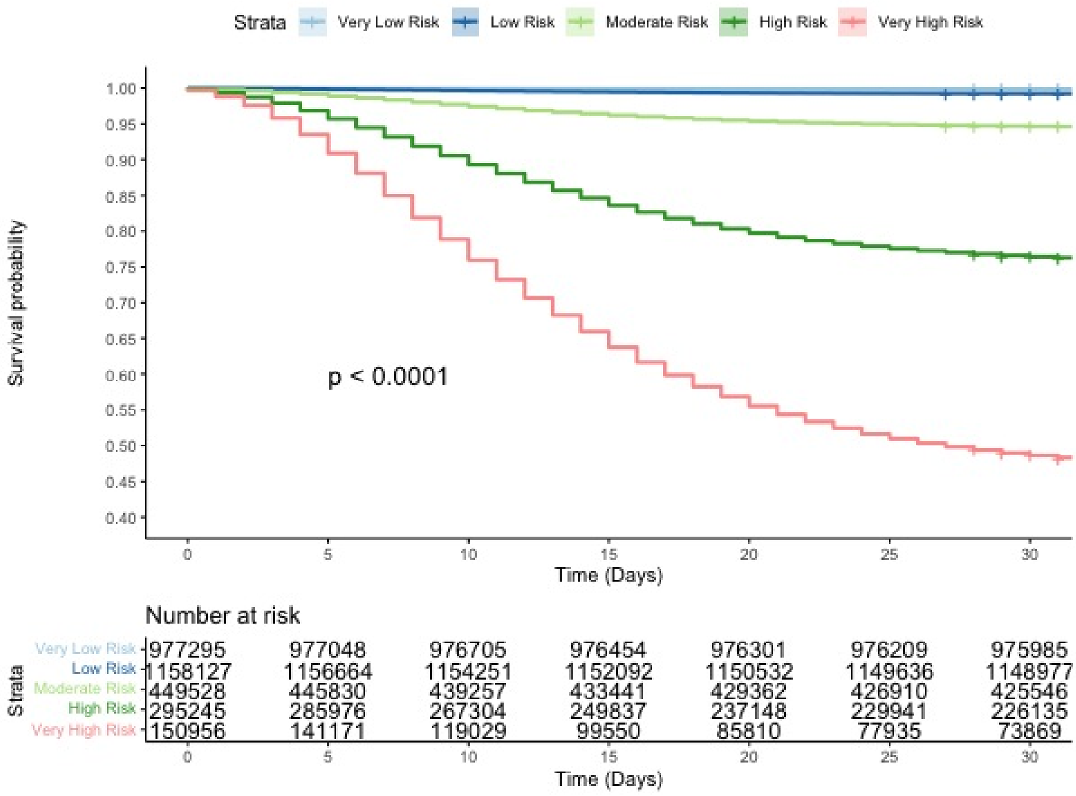
Notes: This figure builds on Figure 6 by displaying the same scatter plot but fitting a linear model (Equation (1)) to multiple subgroups of complex COVID-19 patients separately based on the estimated cutpoints of ages 32 and 77 as discussed in Section 4.2. Panel A covers patients between ages 19 and 90 as in 6 with one cutpoint at age 32; Panel B shows the same scatter plot as in Panel A but with an additional cutpoint at age 77; the points are colored by age groups where `Young`: 18–32, `Middle`: 33–77, and `Old`: 78-90. This figure suggests that intubation rate (or chance of patients receiving intubation) may not vary linearly with mortality risk (proxies by NIR) or age. Section 5 provides more in-depth discussion.

Figure 8: Kaplan-Meier Survival Plots

(a) Training Set



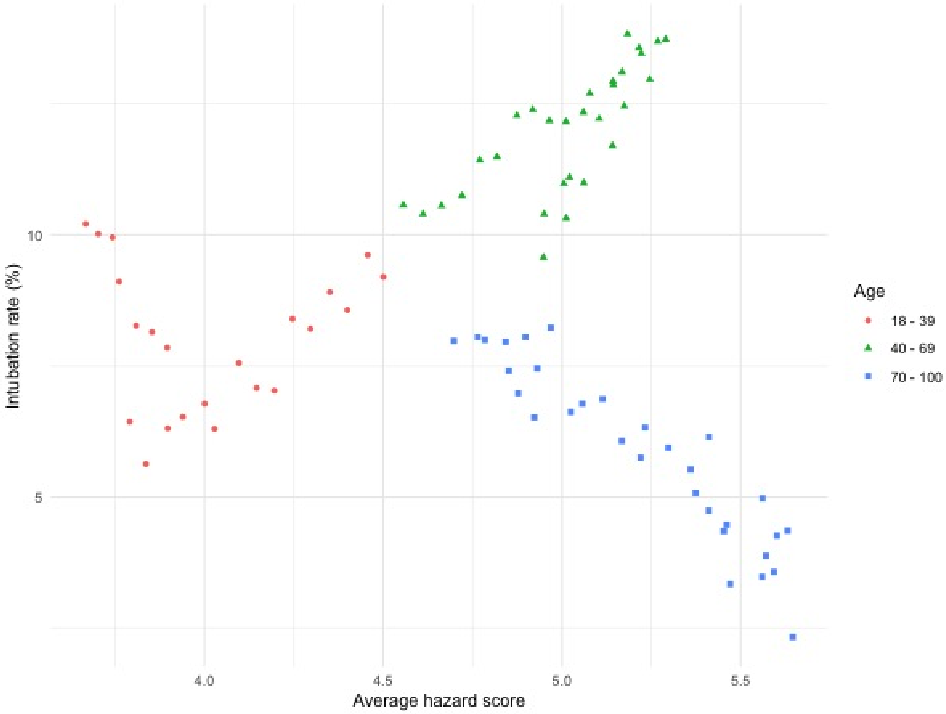
(b) Test Set



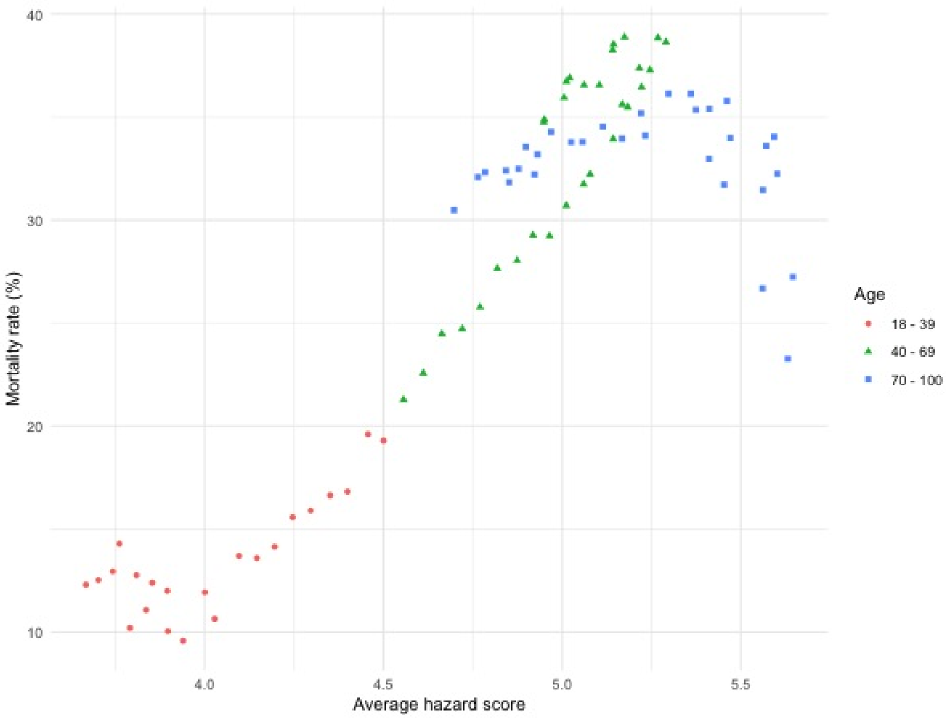
Notes: This figure displays the Kaplan-Meier survival plots that are derived from Cox regression models developed in Section 5.1. Panel A presents the plot for the training set ($n = 2,968,621$) and Panel B presents the plot for the test set ($n = 742,155$). The $p-$values are for the log rank test.

Figure 9: Outcomes of Patients Belonging to High or Very Risk Categories

(a) Intubation Rates

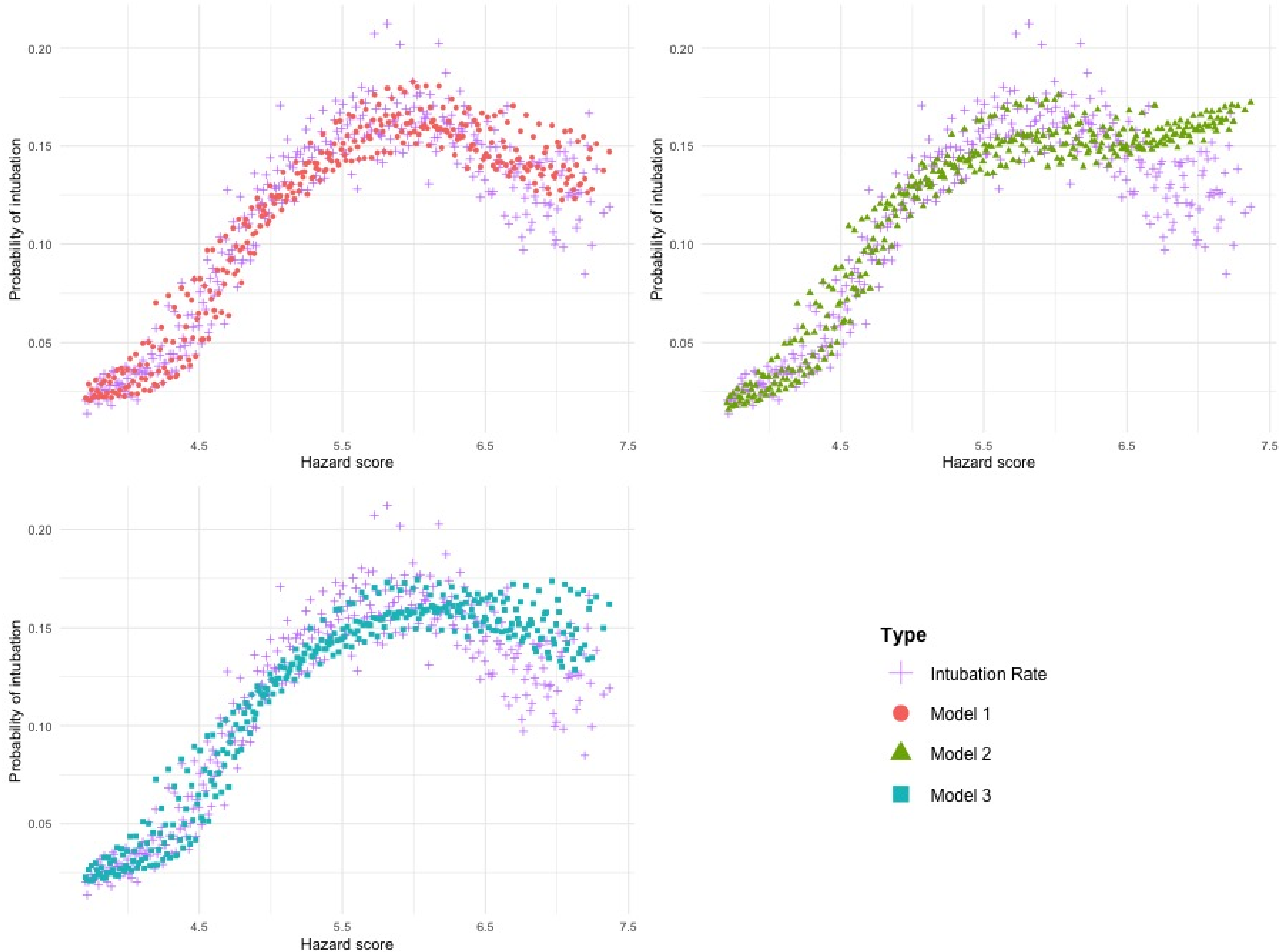


(b) Mortality Rates



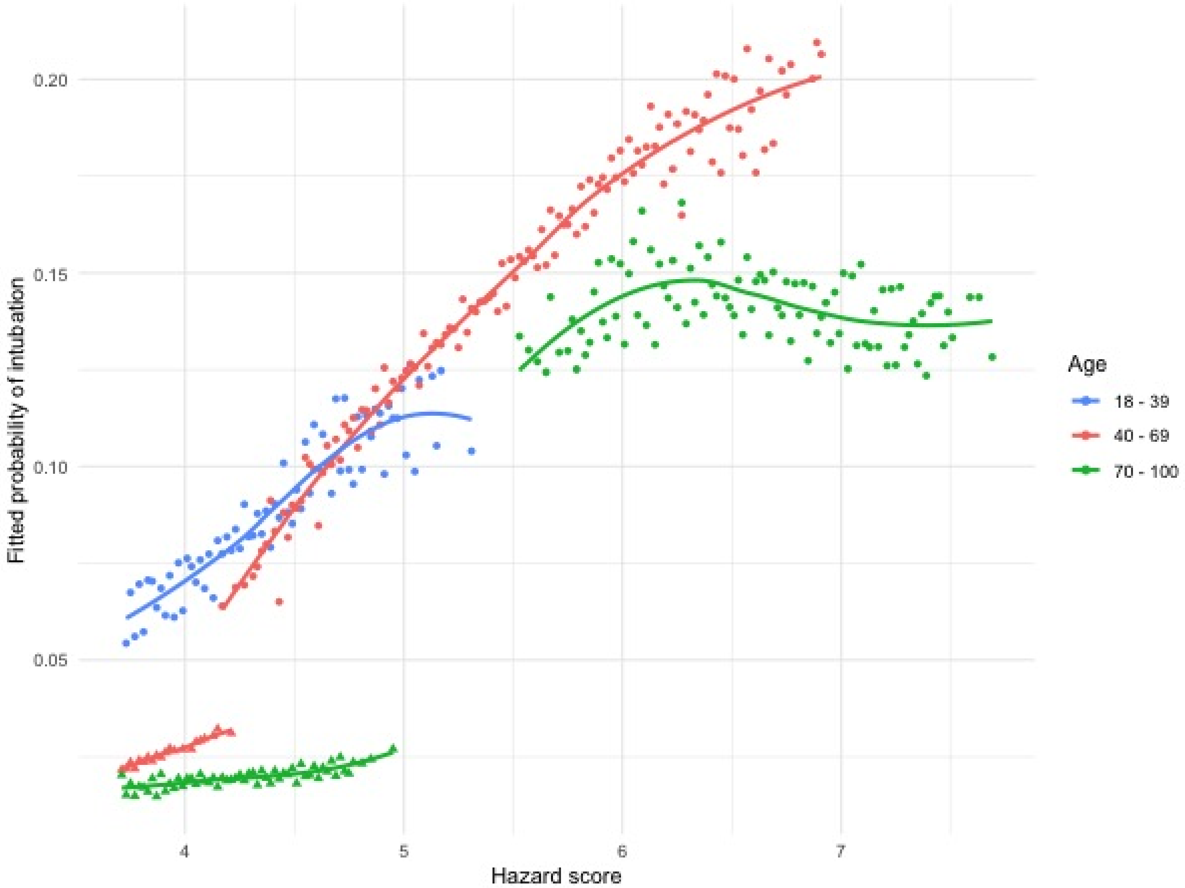
Notes: This figure displays the average intubation rates (Panel A) and average death rates (Panel B) of patients in the "high risk" or "very high risk" categories ($n = 558,386$) across age levels (age range is 18–100). Panel A shows findings that agree with those in Section 4.2 – average intubation rates are slightly flatter for patients aged below 40, then increases until around 69, and then decreases. From Panel B, we see that average mortality rates are stable for patients at either end of the age range and increasing in between, which shows that the mortality risk is somewhat homogeneous. The fact that I am analyzing patients from two categories actually undermine the goal of controlling for mortality risk, however, for the sake of having enough observations in each age-hazard score subgroups, it is ideal to study the current sample of interest.

Figure 10: True and Fitted Probability of Intubation Among High and Very High Risk Patients



Notes: This figure displays the true intubation rates and fitted average intubation probabilities by Equation (9) through (11) labelled as Model 1 through 3 respectively, among high and very high risk COVID-19 patients across ages 18 and 100 ($n = 558,386$). The intubation rates are calculated as number of patients intubated divided by total number of patients, among 0.01 intervals of hazard score; the fitted average intubation probabilities are also taken from the same 0.01 intervals of hazard scores which range from 3.7 to 7.4. Intervals that have less than 10 intubated patients are excluded. Appendix B presents more in-depth discussion of the fitted probabilities including causes of the discontinuity of fitted probabilities that happens around score 4.25.

Figure 11: Fitted Probability of Intubation Among High and Very High Risk Patients, by Age Categories



Notes: This figure displays the fitted average intubation probabilities by Equation (9), among high and very high risk COVID-19 patients across ages 18 and 100 divided into three age groups($n = 558,386$). The fitted average intubation probabilities are calculated from 0.02 intervals of hazard scores which range from 3.7 to 7.4. Intervals that have less than 5 intubated patients are excluded. Data points are then fitted with LOESS curves. Note that the lower left corner where fitted probability of intubation is below 0.05 contain mostly patients that do not have pneumonia.

Table 1: Data Description for Selected Variables

Variable	Description
Sector	Category of institution of the National Health System that provided care (for example, the Mexican Institute of Social Security, the Health Secretary, or the private sector)
State of Mexico	State of Mexico where the medical unit that provided care is located; there are 32 states in total
Age	Years of age of the patient
Male	Dummy for whether the patient is male
Smoking habit	Dummy for whether the patient has a history of smoking
PCR result	Dummy for PCR test result reported by the laboratory of the National Network of Epidemiological Surveillance Laboratories; identifies whether the patient is COVID-19 positive
Date of symptoms onset	Date on which the patient's symptoms begin
Date of admission	Date on which the patient is admitted to a care unit
Date of death	Date on which the patient died, if applicable
Hospitalization	Dummy for whether the patient received care in a hospital
Intubation	Dummy for whether the patient is given endotracheal intubation
ICU	Dummy for whether the patient is admitted into intensive care unit
Diabetes	Dummy for history of diabetes mellitus
COPD	Dummy for has history of chronic obstructive pulmonary disease (COPD)
Asthma	Dummy for history of bronchial asthma
Hypertension	Dummy for history of arterial hypertension (or high blood pressure)
Cardiovascular disease	Dummy for history of cardiovascular disease
Obesity	Dummy for whether the patient is obese
Chronic kidney disease	Dummy for history of chronic kidney disease (CKD)
Other chronic comorbidities	Dummy for history of other chronic comorbidities
Pneumonia	Dummy for whether pneumonia is diagnosed
Immunosuppression	Dummy for whether immunosuppression is diagnosed

Note: This table describes a selected set of variables that are deemed relevant in the Mexican General Directorate of Epidemiology data (Martos-Benítez et al., 2021).

Table 2: Data Selection

Sample step and description	Observations Dropped	Observations Remaining
Identify patients who are suspected to have contracted viral respiratory disease including COVID-19.		7,042,816
Drop patients whose ages are 120 or above as these cases are suspected to be data errors (among these 74 patients, none has died from COVID-19 and 35 are males which is implausible).	74	7,042,742
Drop patients whose dates of death are earlier than dates of entry.	559	7,042,183
Drop patients missing intubation and ICU admission data.	10,841	7,031,342
Select patients who are COVID-19 positive (SARS-CoV-2 RT-PCR positive).	3,012,028	4,019,314

Note: This table describes key sample selection steps, the observations dropped, and the observations remaining after each step. Note that the last step is provided for your information only; patients who are COVID-19 negative may still be studied. The Mexican Secretary of Health defines a suspected case as someone who, in the last 7 days, has presented with at least two of the following: cough, fever, or headache, accompanied by dyspnea, arthralgias, myalgias, sore throat, rhinorrhea, conjunctivitis, or chest pain. (Bello-Chavolla et al., 2020b).

Table 3: Characteristics of COVID-19 Positive Patients

Parameter	All Patients (N = 4,019,314)	Intubated Patients (N = 73,408)	Non-intubated Patients (N = 3,945,906)
Baseline and demographic			
Median age (IQR)	40 (29–53)	60 (48–70)	40 (29–53)
Male (%)	1942456 (48.3)	46530 (63.4)	1895926 (48.0)
Smoking habit (%)	317911 (7.9)	6238 (8.5)	311673 (7.9)
Asthma	103287 (2.6)	1495 (2.0)	101792 (2.6)
CKD (%)	66481 (1.7)	4360 (5.9)	62121 (1.6)
COPD (%)	46050 (1.1)	2862 (3.9)	43188 (1.1)
CVD (%)	68387 (1.7)	4013 (5.5)	64374 (1.6)
Diabetes (%)	466875 (11.6)	24635 (33.6)	442240 (11.2)
Hypertension (%)	627689 (15.6)	29179 (39.7)	598510 (15.2)
Obesity (%)	536585 (13.4)	17548 (23.9)	519037 (13.2)
During course of disease			
Hospitalization (%)	658602 (16.4)	73408 (100.0)	585194 (14.8)
Mechanical ventilation (%)	73408 (1.8)	–	–
ICU Admission (%)	51877 (1.3)	25923 (35.3)	25954 (0.7)
Immunosuppression (%)	41343 (1.0)	2280 (3.1)	39063 (1.0)
Pneumonia (%)	452331 (11.3)	60401 (82.3)	391930 (9.9)
Mortality	244312 (6.1)	55545 (75.7)	188767 (4.8)

Note: This table describes characteristics of COVID-19 positive, COVID-19 positive and intubated, and COVID-19 positive and not intubated patients. Abbreviations: *IQR*, interquartile range; *CKD*, chronic kidney disease; *COPD*, chronic obstructive pulmonary disease; *CVD*, cardiovascular disease; *ICU*, intensive care unit.

Table 4: Time-related Statistics of Five Groups of COVID-19 Patients

	All Patients	Mortality	Mortality Without Hospitalization	Mortality In Hospital Without ICU	Mortality In Hospital Without Intubation
Age mean (SD)	41.88 (17.27)	63.03 (15.10)	62.37 (15.05)	63.44 (14.86)	63.93 (14.92)
Age median (IQR)	40 (29–53)	64 (54–74)	63 (53–73)	65 (54–74)	65 (55–74)
TTM mean (SD)	3.62 (17.27)	5.03 (15.10)	4.68 (15.05)	5.01 (14.86)	5.06 (14.92)
TTM median (IQR)	3 (1–5)	4 (2–7)	4 (2–7)	4 (2–7)	4 (2–7)
TTD mean (SD)	–	13.66 (15.10)	14.80 (15.05)	13.16 (14.86)	12.84 (14.92)
TTD median (IQR)	–	12 (7–18)	12 (7–19)	11 (7–17)	11 (7–17)
LOS mean (SD)	–	8.63 (15.10)	10.12 (15.05)	8.14 (14.86)	7.78 (14.92)
LOS median (IQR)	–	6 (2–12)	7 (2–14)	6 (2–11)	5 (2–11)
N	4019340	244312	18782	200805	169985

Notes: This table reports three types of time-related statistics of five groups of patients who are all COVID-19 positive but received different treatment. This table aims to compare the window of opportunity to treat patients who died without critical care and it reveals that the time elapsed between symptoms onset and mortality of patients who did not receive advanced care (columns 3 to 5) is comparable to that of patients who did. Note that TTD and LOS data are only available for patients who died. Abbreviations: *SD*, standard deviation; *IQR*, interquartile range; *TTM*, time to medical contact (number of days elapsed between symptoms onset and medical contact); *TTD*, time to death (number of days elapsed between symptoms onset and death); *LOS*, length of stay (time elapsed between medical contact and death).

Table 5: Comparison of Characteristics between Complex COVID-19 Patients and Others

Parameter	All Patients ($N = 7,031,342$)	COVID-19 Patients ($N = 4,019,314$)	Complex COVID-19 Patients ($N = 54,550$)
Baseline and demographic			
Median age (IQR)	39 (28–52)	40 (29–53)	65 (55–75)
Male (%)	3379117 (48.1)	1942456 (48.3)	29559 (54.2)
Smoking habit (%)	564626 (8.0)	317911 (7.9)	7888 (14.5)
Asthma	161838 (2.3)	103287 (2.6)	2268 (4.2)
CKD (%)	85931 (1.2)	66481 (1.7)	26549 (48.7)
COPD (%)	61775 (0.9)	46050 (1.1)	15431 (28.3)
CVD (%)	92007 (1.3)	68387 (1.7)	21074 (38.6)
Diabetes (%)	685268 (9.7)	466875 (11.6)	33955 (62.2)
Hypertension (%)	931096 (13.2)	627689 (15.6)	44665 (81.9)
Obesity (%)	798592 (11.4)	536585 (13.4)	16415 (30.1)
During course of disease			
Hospitalization (%)	759653 (10.8)	658602 (16.4)	46753 (85.7)
Mechanical ventilation (%)	83571 (1.2)	73408 (1.8)	6844 (12.5)
ICU Admission (%)	56085 (0.8)	51877 (1.3)	4197 (7.7)
Immunosuppression (%)	54423 (0.8)	41343 (1.0)	6735 (12.3)
Pneumonia (%)	524071 (7.5)	452331 (11.3)	46613 (85.5)
Mortality	289939 (4.1)	244312 (6.1)	23976 (44.0)

Note: This table presents and compares characteristics of complex COVID-19 patients with other groups of patients. “All patients” refer to all patients who has suspicion of carrying viral respiratory disease, including COVID-19 *negative* patients. Abbreviations: *IQR*, interquartile range; *CKD*, chronic kidney disease; *COPD*, chronic obstructive pulmonary disease; *CVD*, cardiovascular disease; *ICU*, intensive care unit.

Table 6: Clinical Outcomes of COVID-19 Patients by Age Groups and Risks

Age group	N	Intubation (%)	ICU (%)	Mortality (%)	Non-intubated Share of Mortality (%)
Complex patients					
[0 − 9]	93	9 (9.68)	7 (7.53)	13 (13.98)	8 (61.54)
[10 − 19]	227	23 (10.13)	11 (4.85)	23 (10.13)	13 (56.52)
[20 − 29]	1417	109 (7.69)	64 (4.52)	309 (21.81)	234 (75.73)
[30 − 39]	2496	234 (9.38)	154 (6.17)	693 (27.76)	529 (76.33)
[40 − 49]	4940	581 (11.76)	356 (7.21)	1680 (34.01)	1220 (72.62)
[50 − 59]	9970	1248 (12.52)	753 (7.55)	3948 (39.6)	2936 (74.37)
[60 − 69]	14352	1987 (13.84)	1132 (7.89)	6647 (46.31)	4991 (75.09)
[70 − 79]	12612	1762 (13.97)	1049 (8.32)	6387 (50.64)	4880 (76.41)
[80 − 89]	7205	792 (10.99)	574 (7.97)	3644 (50.58)	2981 (81.81)
[90 − 99]	1208	96 (7.95)	94 (7.78)	620 (51.32)	539 (86.94)
[100 − 109]	30	3 (10)	3 (10)	12 (40)	10 (83.33)
All patients					
[0 − 9]	87813	2567 (2.92)	3586 (4.08)	1390 (1.58)	785 (56.47)
[10 − 19]	184198	892 (0.48)	964 (0.52)	835 (0.45)	538 (64.43)
[20 − 29]	776790	2087 (0.27)	2192 (0.28)	3620 (0.47)	2655 (73.34)
[30 − 39]	900718	4607 (0.51)	4183 (0.46)	10073 (1.12)	7350 (72.97)
[40 − 49]	799416	9782 (1.22)	7371 (0.92)	25819 (3.23)	18961 (73.44)
[50 − 59]	621630	16188 (2.6)	10698 (1.72)	49485 (7.96)	36949 (74.67)
[60 − 69]	365534	18802 (5.14)	11168 (3.06)	66367 (18.16)	50809 (76.56)
[70 − 79]	191078	12972 (6.79)	7686 (4.02)	55186 (28.88)	44007 (79.74)
[80 − 89]	77837	4907 (6.3)	3466 (4.45)	26957 (34.63)	22660 (84.06)
[90 − 99]	13486	578 (4.29)	529 (3.92)	4458 (33.06)	3949 (88.58)
[100 − 109]	736	25 (3.4)	33 (4.48)	121 (16.44)	103 (85.12)

Notes: This table summarizes and compares the clinical outcomes (with percentages in brackets) of all and complex COVID-19 patients as defined in Section 4.1 ($n = 54,550$). "Not intubated share of mortality" refers to number of patients who died without receiving intubation (# of patients died and not intubated/# of patients died). Abbreviation: *ICU*, intensive care unit.

Table 7: Linear and Quadratic Estimates

	Dependent variable:	
	IR	
	(1)	(2)
$NIDR$	0.099***	0.923***
	(0.029)	(0.178)
$NIDR^2$		−0.013***
		(0.003)
Constant	7.590***	−4.201
	(0.940)	(2.841)
Observations	78	78
R^2	0.177	0.475
Adjusted R^2	0.167	0.461
Note:	*p<0.1; **p<0.05; ***p<0.01	

Notes: This table reports estimates from linear (1) and quadratic (2) regressions of intubation rates as specified in Equation (1) and (2) across ages 18 and 100 (18, 97–100 are excluded due to not enough data). We note that the quadratic specification (column (2)) fits the data much more closely, suggesting a quadratic (inverted U-shaped) relationship between IR and $NIDR$. Heteroskedasticity-robust standard errors are in brackets. Abbreviations: *IR*, intubation rate; *NIDR*, non-intubated death rate. *p<0.1; **p<0.05; ***p<0.01.

Table 8: Cox Proportional Risk Models for Mortality

Model	Parameter	Coef.	SE	Wald	HR	95% CI	P-value
Individual predictors	Age	0.045	0.000	285.079	1.046	1.05–1.05	< 0.001
C-statistic = 0.917	Diabetes	0.297	0.005	57.315	1.346	1.33–1.36	< 0.001
	CKD	0.400	0.009	45.383	1.492	1.47–1.52	< 0.001
	Hypertension	0.147	0.005	27.959	1.158	1.15–1.17	< 0.001
	Immunosuppression	0.202	0.014	14.081	1.224	1.19–1.26	< 0.001
	Obesity	0.218	0.006	38.137	1.244	1.23–1.26	< 0.001
	Pneumonia	2.381	0.006	431.740	10.816	10.7–10.93	< 0.001
	Other comorbidity	0.262	0.010	26.465	1.299	1.27–1.32	< 0.001
	Male	0.371	0.005	78.020	1.449	1.44–1.46	< 0.001
Score point	One-point increment	1.000	0.001	703.828	2.718	2.71–2.73	< 0.001
C-statistic = 0.917							
Risk categories	Very low risk	Reference					
C-statistic = 0.906	Low risk	1.888	0.030	62.346	6.607	6.23–7.01	< 0.001
	Moderate risk	3.839	0.029	131.491	46.462	43.88–49.2	< 0.001
	High risk	5.429	0.029	188.839	228.008	215.52–241.23	< 0.001
	Very high risk	6.405	0.029	222.920	604.832	571.71–639.87	< 0.001

Notes: This table reports estimates from three Cox proportional risk models for mortality in a randomly selected training set containing 80% of the COVID-19 positive patients. The three models use individual predictors, the COVID-19 hazard score as discussed in Section 5.1, and risk categories respectively. Note that the coefficient of one-point increment in score point is 1 by construction. Asthma, cardiovascular disease and COPD are not included because they turn out to be "protective" when included (i.e., reduces mortality risk), likely due to unexplained correlation between them and demographics of patients. Abbreviations: *Coef.*, coefficients; *SE*, standard error; *HR*, hazard ratio; *CI*, confidence interval; *CKD*, chronic kidney disease; *COPD*, chronic obstructive pulmonary disease.

Table 9: Characteristics of COVID-19 Patients By Risk Categories

Parameter \ Risk Category	Very low	Low	Moderate	High	Very high
Age range	18–38	18–61	18–82	18–100	35–100
Median age (IQR)	27 (24–31)	43 (38–48)	59 (55–65)	57 (45–73)	71 (65–78)
Intubation (%)	729 (0.06)	2829 (0.19)	5918 (1.03)	30028 (8.06)	29332 (15.49)
ICU (%)	1034 (0.09)	2117 (0.15)	3382 (0.59)	21398 (5.74)	18532 (9.79)
Mortality (%)	1537 (0.13)	11762 (0.81)	31773 (5.51)	91890 (24.67)	102203 (53.98)
N	1191819	1458739	576571	372464	189345

Notes: This table reports the age characteristics and clinical outcomes of COVID-19 patients aged between 18 and 100 categorized by risk levels ($n = 3,788,938$). Note that the "high" risk category spans across the entire age range of patients that are studied. Abbreviation: *IQR*, interquartile range; *ICU*, intensive care unit.

Table 10: Heteroskedastic Probit Estimates

	Dependent variable:					
	Intubation			Death		
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.002^{*}		0.004^{**}	0.033^{***}		0.010^{***}
	(0.001)		(0.002)	(0.005)		(0.001)
Age^2			-0.0001^{***}			-0.0001^{***}
			(0.00002)			(0.00001)
Hazard score		0.339^{***}	0.433^{***}		0.409^{***}	0.517^{***}
		(0.029)	(0.030)		(0.031)	(0.027)
Age $<$ 40	0.057	-0.526^{***}		0.835^{***}	-0.587^{***}	
	(0.039)	(0.092)		(0.156)	(0.066)	
Age $\geq$ 70	2.761^{***}	0.481^{***}		1.802^{***}	0.383^{***}	
	(0.986)	(0.117)		(0.574)	(0.056)	
Diabetes	0.023			0.187^{***}		
	(0.016)			(0.030)		
CKD	0.011			0.379^{***}		
	(0.010)			(0.064)		
Hypertension	0.001			0.064^{***}		
	(0.004)			(0.015)		
Immunosuppression	0.031			0.227^{***}		
	(0.022)			(0.049)		
Obesity	0.049			0.167^{***}		
	(0.033)			(0.028)		
Pneumonia	3.539^{***}			4.023^{***}		
	(0.424)			(0.454)		
Male	0.030			0.178^{***}		
	(0.020)			(0.028)		
Age $\times$ Age $<$ 40	-0.002			-0.021^{***}		
	(0.001)			(0.004)		
Age $\times$ Age $\geq$ 70	-0.039^{***}			-0.023^{***}		
	(0.014)			(0.008)		
Hazard score $\times$ Age $<$ 40		0.109^{***}			0.124^{***}	
		(0.021)			(0.015)	
Hazard score $\times$ Age $\geq$ 70		-0.114^{***}			-0.080^{***}	
		(0.028)			(0.012)	
Constant	-3.937^{***}	-2.490^{***}	-3.025^{***}	-6.436^{***}	-2.315^{***}	-3.239^{***}
	(0.494)	(0.271)	(0.222)	(0.633)	(0.177)	(0.168)
Observations	372,464	372,099	372,099	372,464	372,464	372,464

Notes: This table reports estimates from heteroskedastic probit regressions of intubation decisions, as specified in Equation (9) to (11) and heteroskedastic probit regressions of death, on patients who are classified as "high risk" ($n = 372,464$). Among columns (1), (2), and (3), specification (1) fits the data the best in terms of Akaike information criterion. The range of age is 18–100; reference age levels are 40–79. Abbreviation: *CKD*, chronic kidney disease. *p<0.1; **p<0.05; ***p<0.01

Appendix

A Non-intubated Death Rate as Proxy for Mortality Risk

In Section 4.2 I proposed that non-intubated death rate ($NIDR$)[22] can be used as a proxy for mortality risk (or death rate). This claim can be validated in two ways, one is to compare $NIDR$ with the actual mortality rate of patients, and another is to assess the association between $NIDR$ and (old) age, which is the single most influential risk factor (Petrilli et al., 2020).

A.1 Non-intubated Death Rate and Death Rate

Table 6 presents the number of patients intubated at different age groups, due to low ratios of patients intubated, the subset of non-intubated patients actually largely resemble the full cohort, and the same applies to $NIDR$ in the sense that it closely follows death rate. Figure A9a shows that $NIDR$ indeed closely follows death rate across different age levels for the full COVID-19 patients cohort and thus is a good proxy for mortality risk. We may also note that $NIDR$ is always below DR, suggesting that as long as intubation has positive effect on patients (in terms of reducing mortality risk), then patients who are intubated tend to be more sick than those who are not on average (and if they are not intubated, their death rates will be even higher).

A.2 Association Between $NIDR$ and Age

We may further verify the idea that $NIDR$ indeed captures the mortality risk of patients by assessing the variation in $NIDR$ and mean age of patients across the 32 states in Mexico; age has been shown to be a important risk factor and hence mean age of a state is a good proxy for mortality risk of its residents, so if $NIDR$ moves closely with mean age in different states, we may say that $NIDR$ is also a good proxy. Using location information of patients (where presumably the location is exogenous), I plot the averages of age of patients in the 32 states in Mexico overlaid by $NIDR$, as shown in Figure A10. We can see that the two variables move very closely together and thus the claim is supported.

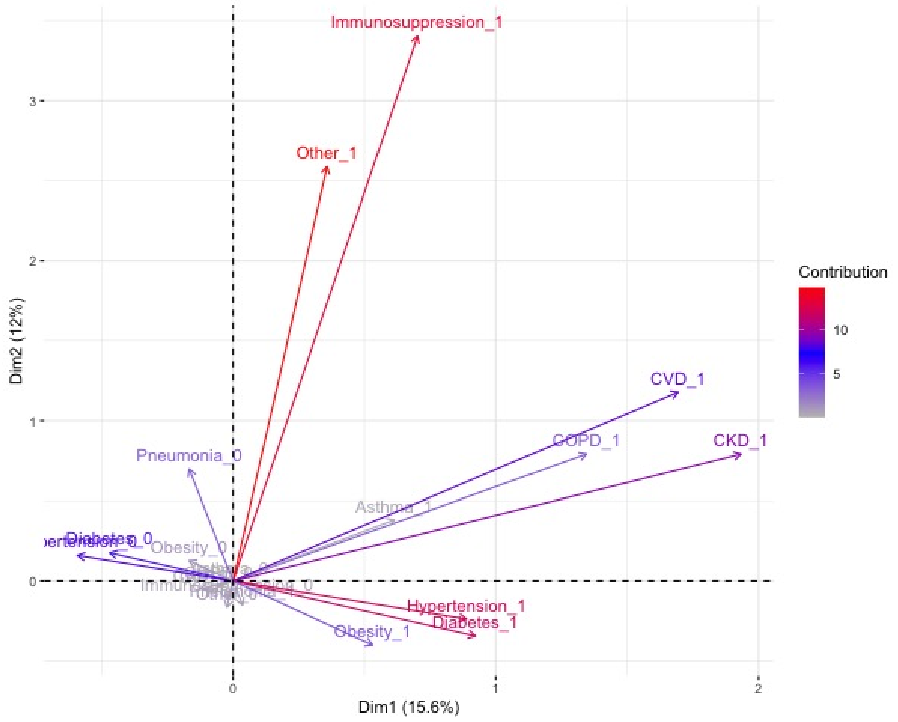
[22] Defined as *number of patients not intubated and died/number of patients not intubated.*

B Assessing Model Fit

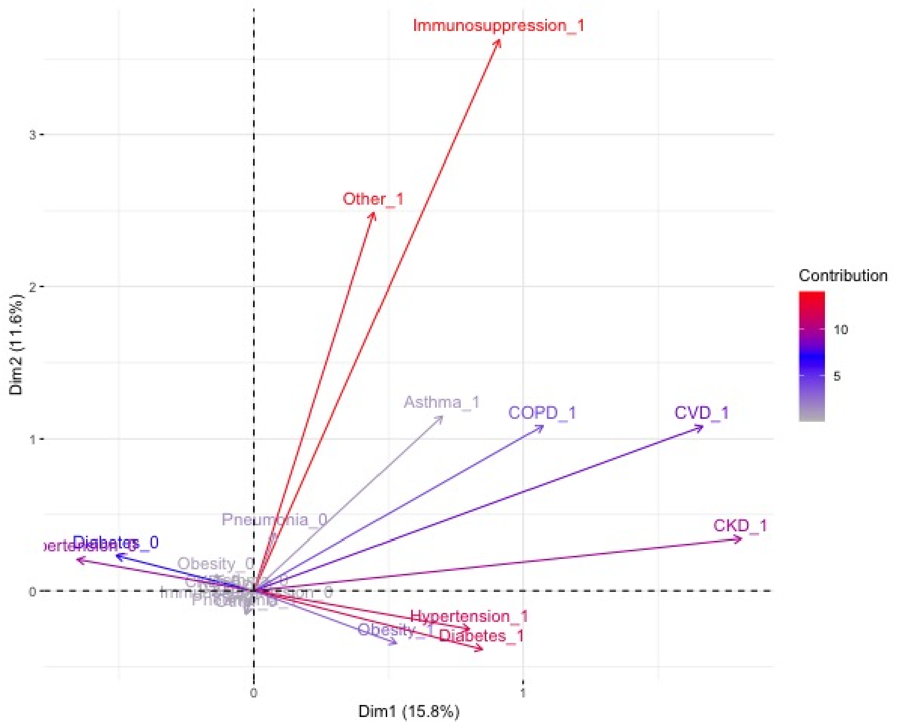
Section 5.3 and Figure 10 present the probabilities of intubation using Equations (9) through (11). In general, all three models could capture the trend in true intubation rates fairly well, however, there exists a distinctive discontinuity in fitted average probabilities of intubation (around hazard score 4.25) that is not seen in the true intubation rates. The presence of the discontinuity is partly due to the limitation of the data where comorbidities are coded as binary variables which inevitably causes the model to make inferences on inputs that are discontinuous to start with. With closer inspection of the fitted probabilities that are presented in Figure A3, we can actually see that the lower left cluster of fitted probabilities represent mostly patients who do not have pneumonia while the upper right cluster represents patients who have pneumonia, causing a discontinuity in fitted average probabilities.

Figure A1: Multiple Correspondence Analysis (MCA) Plots

(a) MCA of COVID-19 Patients Who Received Intubation

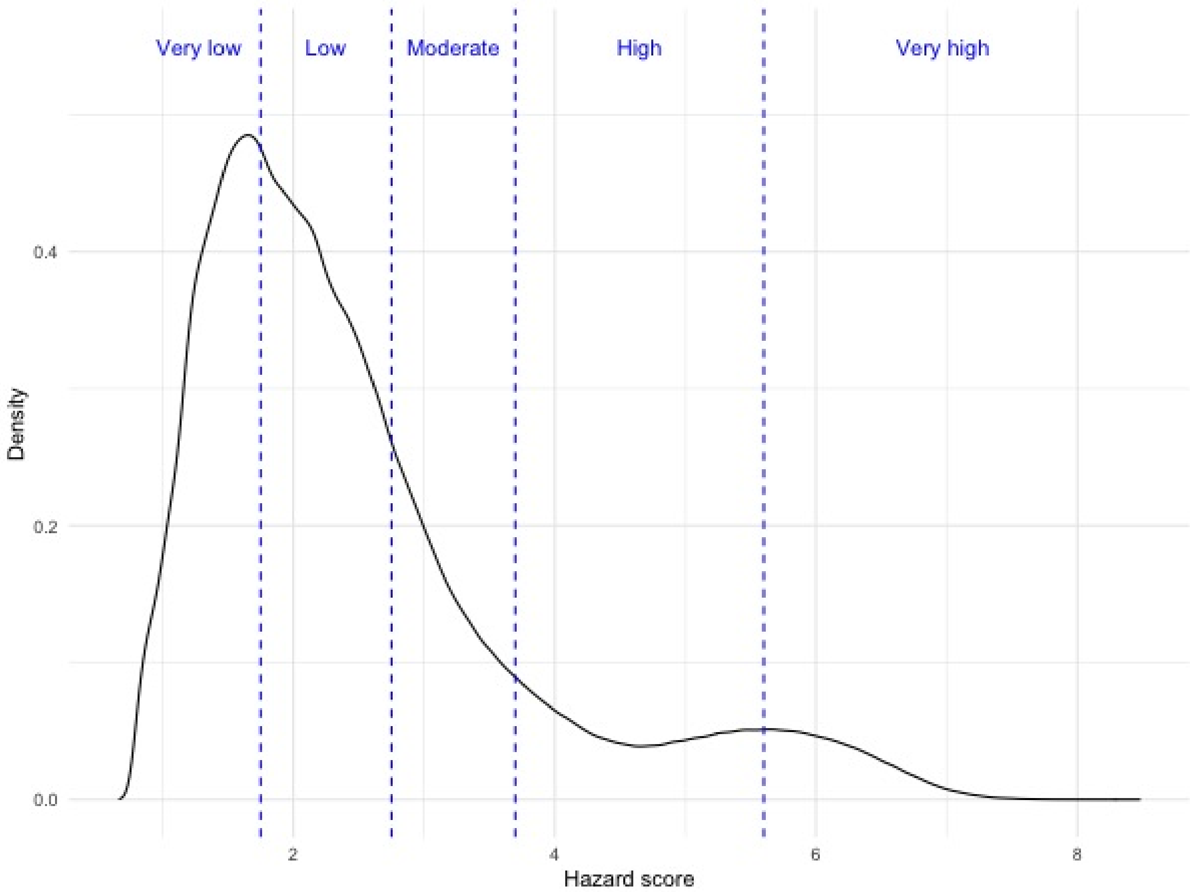


(b) MCA of COVID-19 Patients Who Died



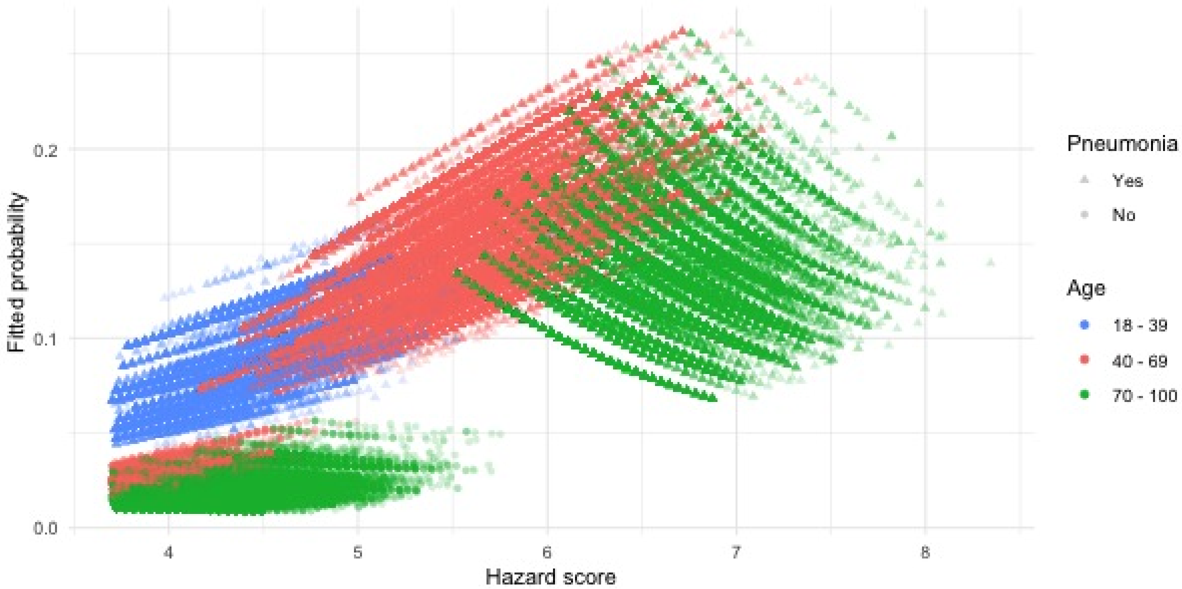
Notes: This figure displays two-dimensional variables plots of the results of MCAs implemented on 9 comorbidities of COVID-19 patients, excluding missing data. Panel A displays analysis of COVID-19 patients who received intubation ($n = 76,741$) and Panel B displays analysis of COVID-19 patients who died ($n = 266,393$). We can see that these results are similar to that in Figure 2. The 9 comorbidities are asthma, cardiovascular disease (cardiovascular), chronic kidney disease (CKD), chronic obstructive pulmonary disease (COPD), diabetes mellitus, hypertension, immunosuppression, obesity and other comorbidity (other). 1 = Yes and 0 = No.

Figure A2: Density Plot of Hazard Scores and Risk Category Cutoffs



Notes: This figure shows distribution of hazard scores of all COVID-19 patients who are in the training set ($n = 3,031,151$) and four cutoffs determined that stratify patients into five risk categories. Starting from the least risky category, each category consists of about 30%, 40%, 15%, 10% and 5% of the patients respectively.

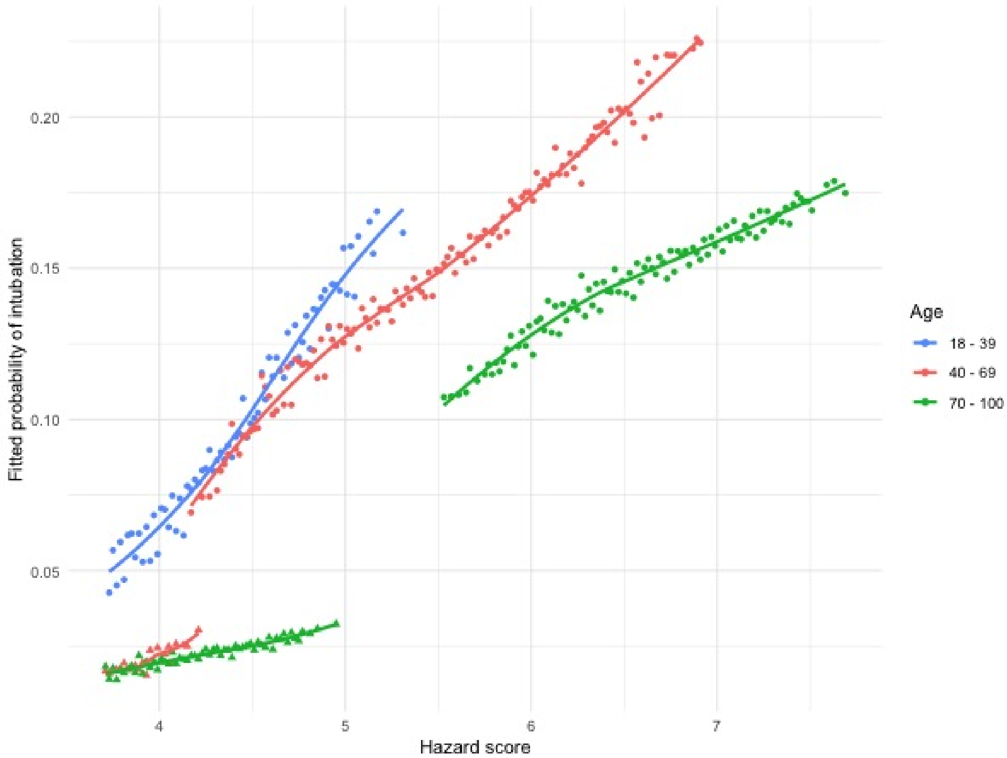
Figure A3: Fitted Probability of Intubation Versus Hazard Score Among High and Very High Risk Patients



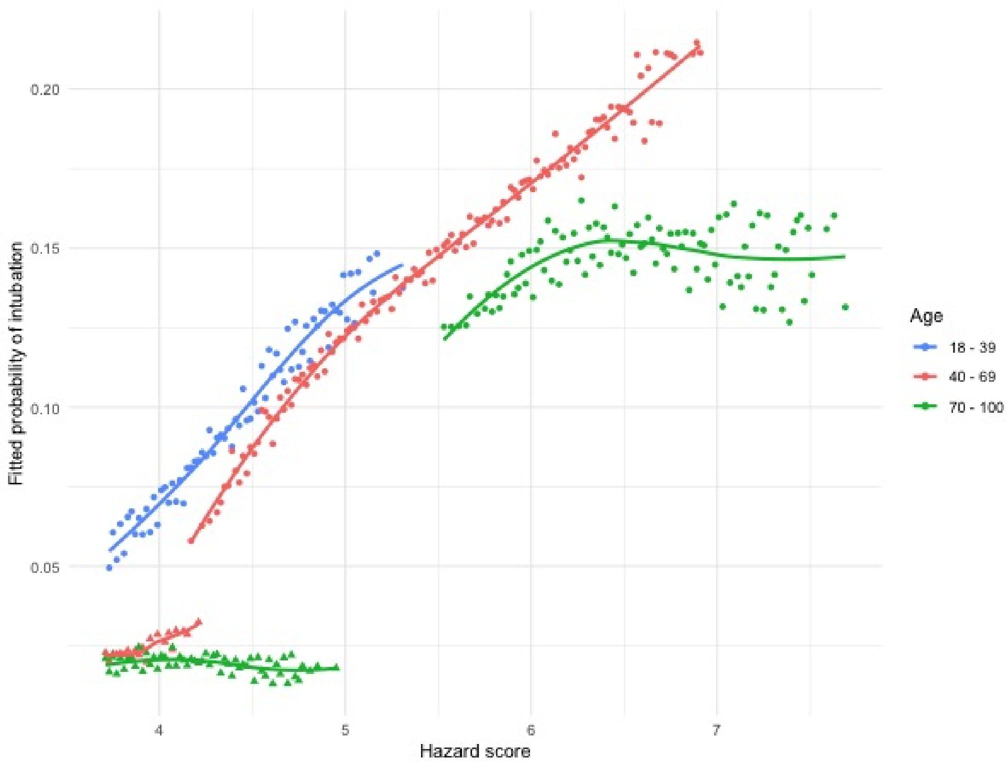
Notes: This figure displays a scatter plot of fitted probability of intubation from Equation (9) versus hazard score of high and very high risk COVID-19 patients across ages 18 and 100 colored by three age groups ($n = 558, 386$). The hazard score of this group of patients rages from 3.7 to 7.4.

Figure A4: Fitted Probability of Intubation Among High and Very High Risk Patients, by Age Categories

(a) Probabilities Fitted By Equation (10)

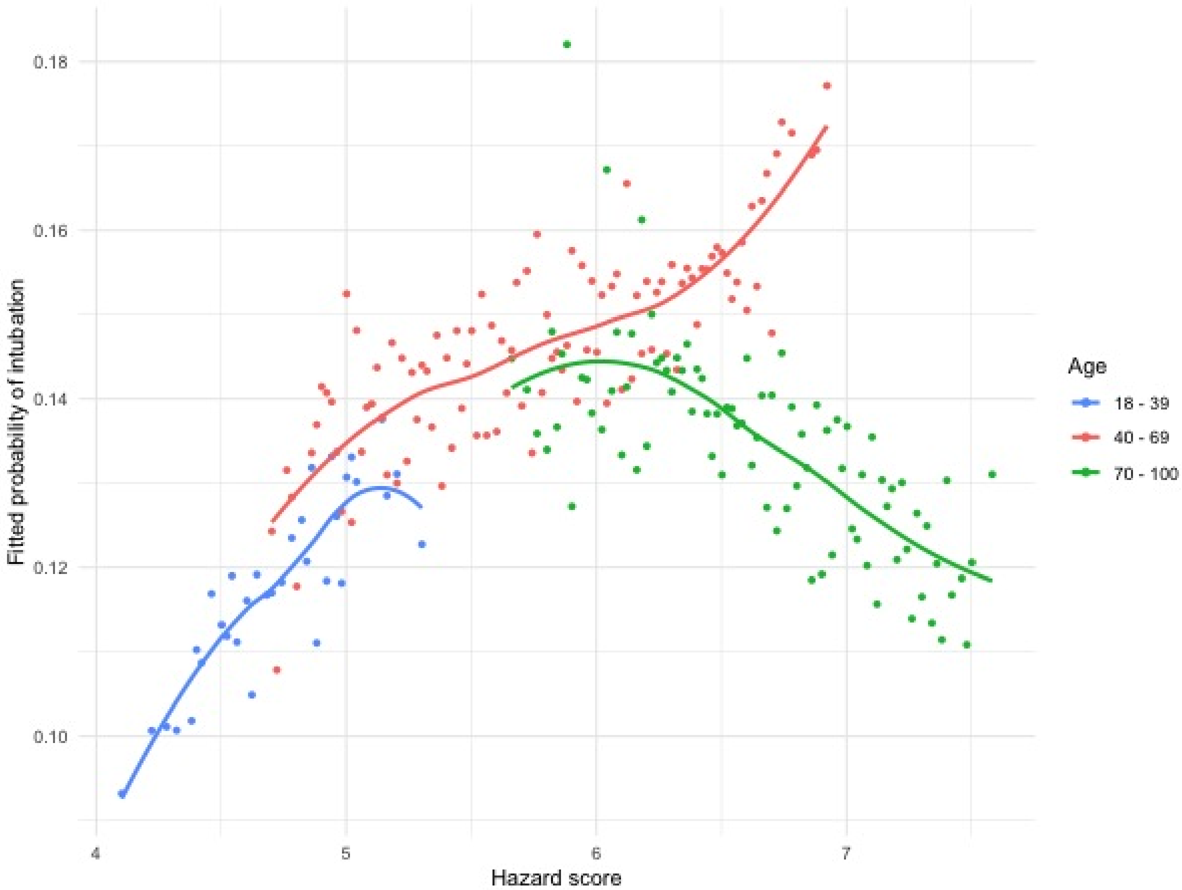


(b) Probabilities Fitted By Equation (11)



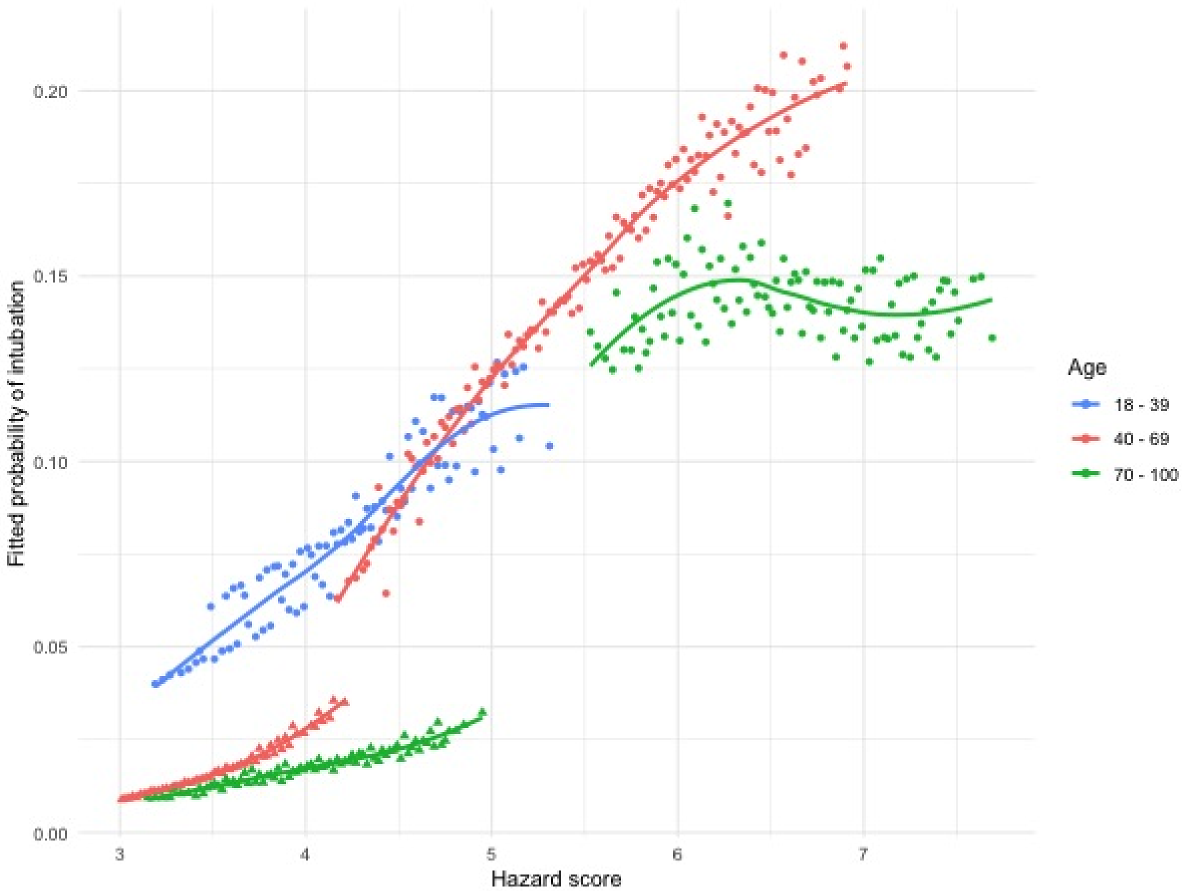
Notes: Similar to Figure 11, this figure displays two scatter plots of fitted probability of intubation versus hazard score of high and very high risk COVID-19 patients across ages 18 and 100 colored by three age groups ($n = 558,386$). The hazard score of this group of patients rages from 3.7 to 7.4.

Figure A5: Fitted Probability of Intubation Among Complex Patients, by Age Categories



Notes: Similar to Figure 11, this figure displays a scatter plot of fitted probability of intubation, using Equation (9), versus hazard score of complex COVID-19 patients across ages 18 and 100 colored by three age groups ($n = 53,636$). The hazard score of this group of patients rages from 4.1 to 7.6. As expected, the patients receive much intubation (i.e., are very high risk) and the trend in intubation exhibits an inverted-U shape. This result aligns fairly well with those in Section 4.2 and Section 5.2.

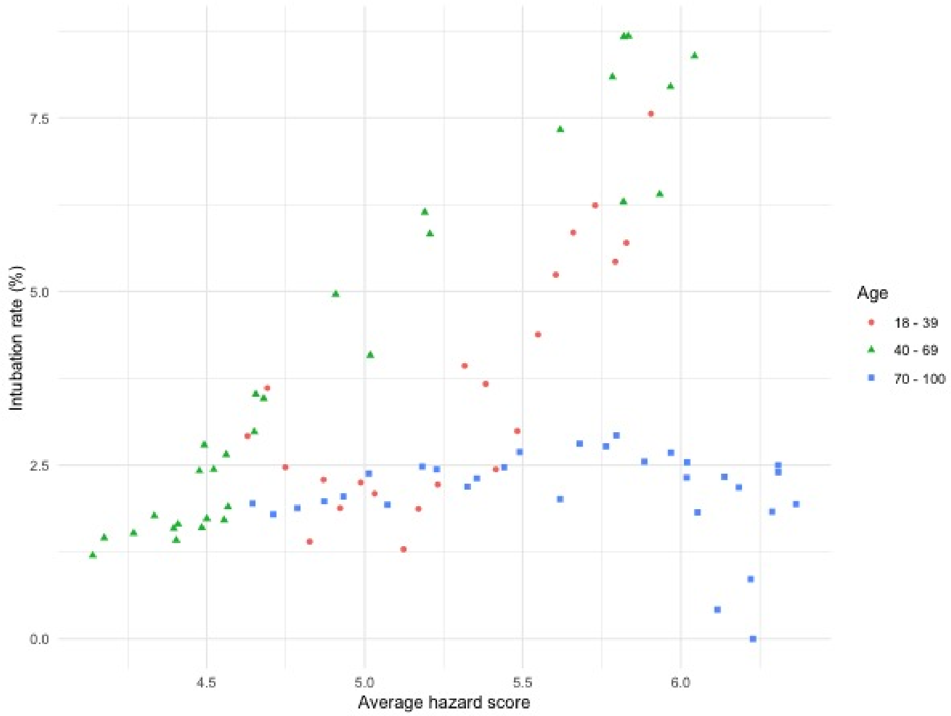
Figure A6: Fitted Probability of Intubation Among Patients Having Hazard Score > 3, by Age Categories



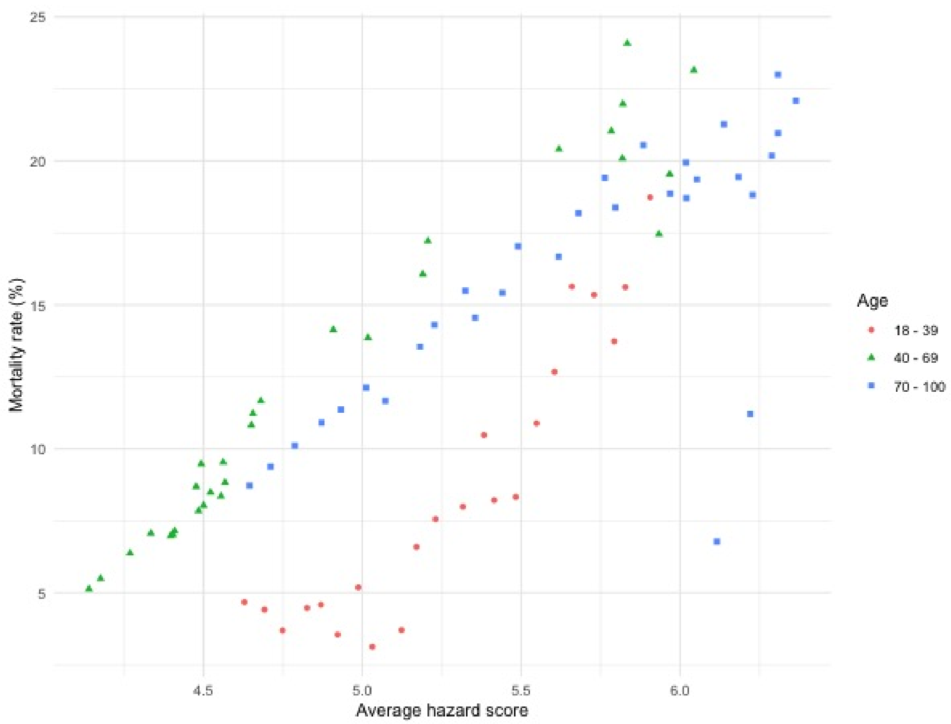
Notes: Similar to Figure 11, this figure displays a scatter plot of fitted probability of intubation, using Equation (9), versus hazard score of moderate to very high risk COVID-19 patients across ages 18 and 100 colored by three age groups ($n = 918, 774$). The hazard score of this group of patients rages from 3 to 7.4. This result aligns fairly well with that in Figure 11, suggesting that the finding is no sensitive to choice of hazard score cutoff.

Figure A7: Outcomes of COVID-19 Negative Patients Belonging to High or Very Risk Categories

(a) Intubation Rates

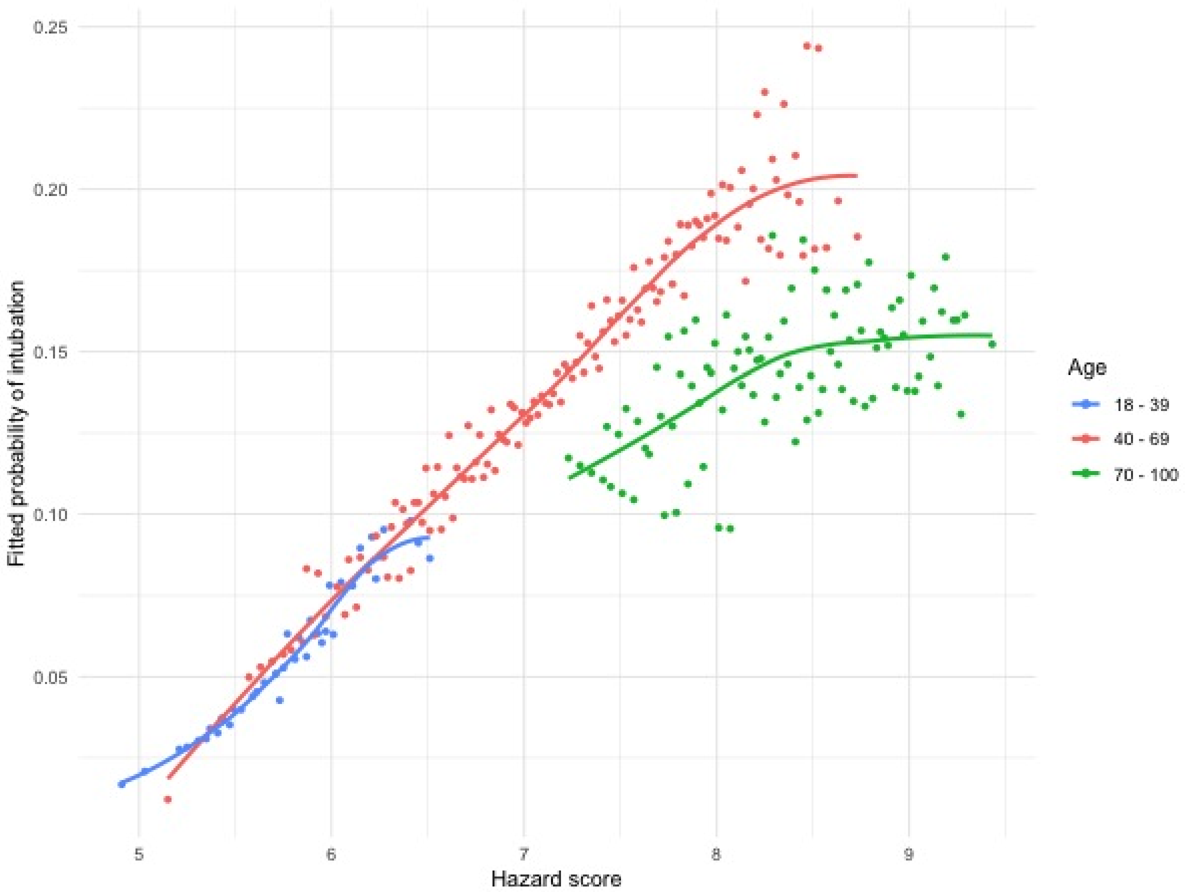


(b) Mortality Rates



Notes: This figure displays the average intubation rates (Panel A) and average death rates (Panel B) of COVID-19 *negative* patients in the "high risk" or "very high risk" categories ($n = 393,301$) across age levels (age range is 18–100). Panel A shows that intubation rates are increasing with respect to average hazard score for young and middle-aged patients but flat for old patients. From Panel B, we see that mortality rates are increasing with respect to hazard score for all age groups as expected.

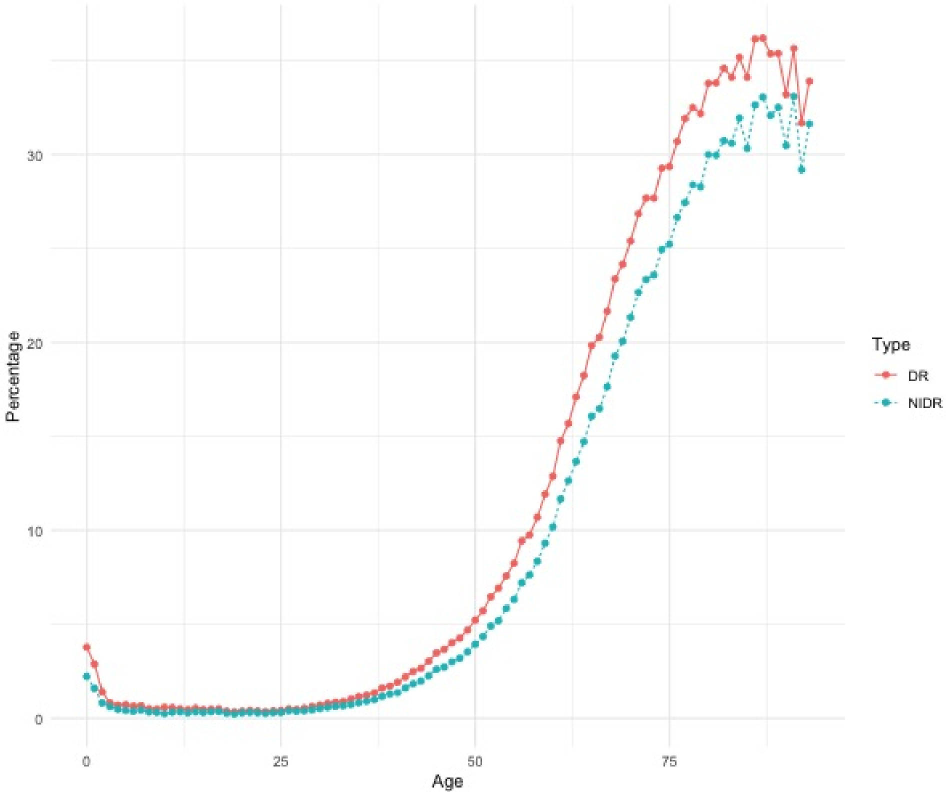
Figure A8: Fitted Probability of Intubation Among High and Very High Risk COVID-19 Negative Patients, by Age Categories



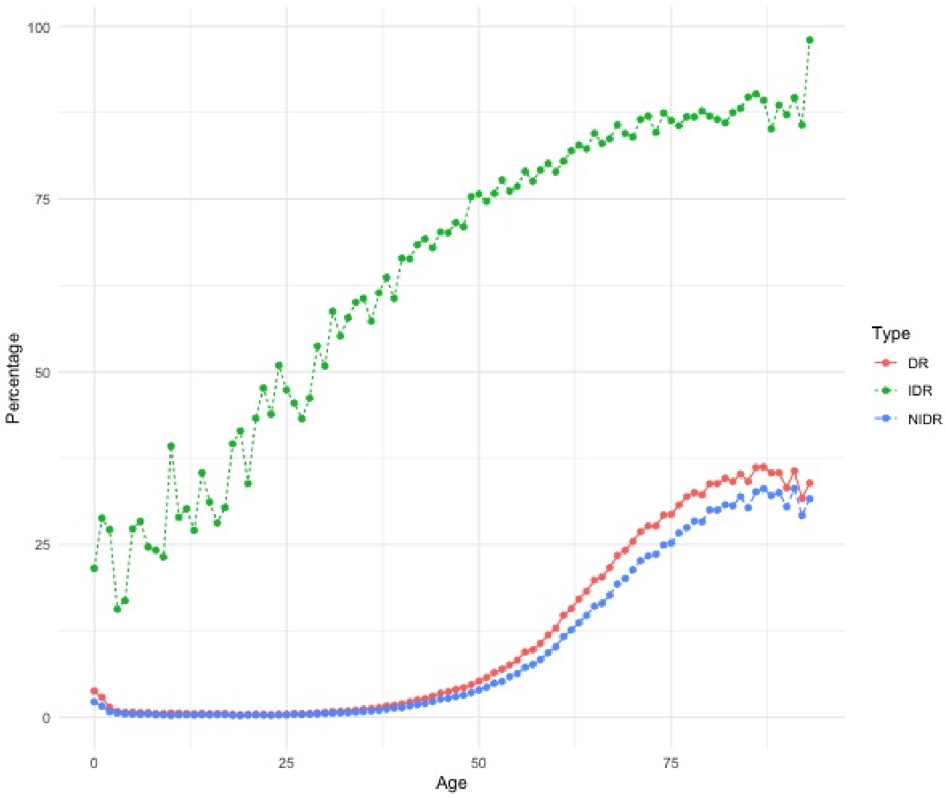
Notes: This figure displays the fitted average intubation probabilities by Equation (9), among high and very high risk COVID-19 *negative* patients across ages 18 and 100 divided into three age groups($n = 393,301$). The fitted average intubation probabilities are calculated from 0.02 intervals of hazard scores above 3.7. Intervals that have less than 5 intubated patients are excluded. Data points are then fitted with LOESS curves.

Figure A9: Outcome Summary by Age

(a) Comparison of Non-intubated Death Rate ($NIDR$) and Death Rate (DR)

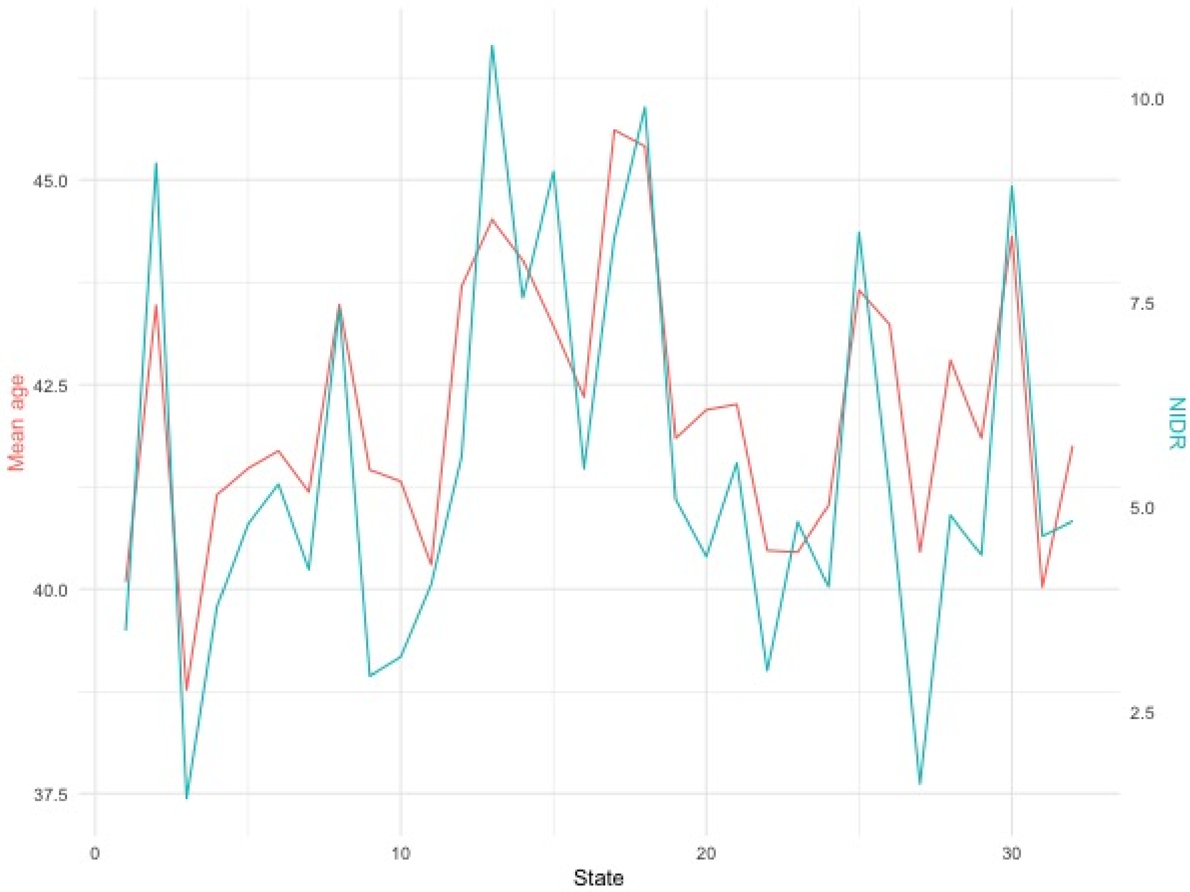


(b) Comparison of $NIDR$ and DR and Intubated Death Rate (IDR)



Notes: This figure shows the comparison between $NIDR$, DR, and IDR across different ages of all COVID-19 patients ($n = 4,019,314$), excluding age levels that have less than 50 patients intubated. The subsetted age range spans from 0 to 97 and only age levels above 97 are omitted. $NIDR = \frac{\text{\# patients not intubated and died}}{\text{\# patients not intubated}}$; $DR = \frac{\text{\# patients died}}{\text{\# patients}}$; $IDR = \frac{\text{\# patients intubated and died}}{\text{\# patients intubated}}$; $\# =$ number of.

Figure A10: Average Age and Non-intubated Death Rate Across 32 States in Mexico



Notes: This figure displays the average age of COVID-19 patients ($n = 4,019,314$) in 32 states of Mexico overlaid with $NIDR$ to show that they move closely with each other, in order to support the claim that $NIDR$ is a good proxy for mortality risk given that age is known to be an influential risk factor (and hence proxy for mortality risk).

Table A1: Characteristics of COVID-19 Negative Patients

Parameter	All Patients (N = $3,012,028$)	Intubated Patients (N = $10,163$)	Non-intubated Patients (N = $3,001,865$)
Baseline and demographic			
Median age (IQR)	38 (27–50)	61 (51–70)	38 (27–50)
Male (%)	1436661 (47.7)	6551 (64.5)	1430110 (47.6)
Smoking habit (%)	246715 (8.2)	887 (8.7)	245828 (8.2)
Asthma	58551 (1.9)	154 (1.5)	58397 (1.9)
CKD (%)	19450 (0.6)	566 (5.6)	18884 (0.6)
COPD (%)	15725 (0.5)	339 (3.3)	15386 (0.5)
CVD (%)	23620 (0.8)	459 (4.5)	23161 (0.8)
Diabetes (%)	218393 (7.3)	3551 (34.9)	214842 (7.2)
Hypertension (%)	303407 (10.1)	4039 (39.7)	299368 (10.0)
Obesity (%)	262007 (8.7)	2209 (21.7)	259798 (8.7)
During course of disease			
Hospitalization (%)	101051 (3.4)	10163 (100.0)	90888 (3.0)
Mechanical ventilation (%)	10163 (0.3)	–	–
ICU Admission (%)	4208 (0.1)	2368 (23.3)	1840 (0.1)
Immunosuppression (%)	13080 (0.4)	242 (2.4)	12838 (0.4)
Pneumonia (%)	71740 (2.4)	8211 (80.8)	63529 (2.1)
Mortality	45627 (1.5)	8586 (84.5)	37041 (1.2)

Note: This table describes characteristics of COVID-19 negative, COVID-19 negative and intubated, and COVID-19 negative and not intubated patients. Abbreviations: *IQR*, interquartile range; *CKD*, chronic kidney disease; *COPD*, chronic obstructive pulmonary disease; *CVD*, cardiovascular disease; *ICU*, intensive care unit.