Master thesis - Policy Economics

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Healthcare supply and regional differences of covid mortality in the US.

This paper comprises an empirical analysis of the relationship of healthcare capacity and regional covid mortality controlled for a large set of medical- and socioeconomic mortality covariates for a year in 3,021 American Counties. An analysis of this relationship is only feasible if supply is defined in multiple dimensions that allow for a division of healthcare input factors (materials, personnel, facilities, and funds). This supply-side model consists of the input factors: hospitals, three type of hospital beds, the use of ventilators, two dimensions of medical personnel, and healthcare expenditures. Hospital bed supply in a pandemic is associated with mortality decreasing if and only if the supply of healthcare services was effectively reallocated to meet short-term intensive care demand. A policymaker should therefore identify which link of the healthcare supply chain is under the most pressure and reallocate capacity towards this mortality decreasing healthcare input factor. Additionally, preparing a swift reallocation of healthcare input factors may have beneficial effects in the event of a future surge in healthcare demand.

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I - Introduction

American hospitals have been overloaded with patients requiring healthcare services at times during the COVID-19 pandemic. One recent example is the hospitals in Sacramento County, Los Angeles. Last December, all intensive care beds (ICU) were filled, and no additional beds were available for most Southern Californians (Bernstein, 2020). In spring 2020, hospitals in New York City were overwhelmed by the early outbreak and had a shortage of ventilators to treat infected patients (BBC News, 2020). As of writing, it has been over a year that the World Health Organization (WHO) characterized the COVID-19 outbreak as a pandemic (WHO, 2020). Even though vaccines are society's getaway ticket out of this pandemic, the death toll has been considerable. The number of COVID-19 infections in the United States (US) has surpassed the 30 million mark, with the number of deaths around 560.000**.** The impact of the COVID-19 outbreak is heterogeneous across the States. For instance, the case-fatality ratio (CFR) of COVID-19 patients, the fraction of positive cases who die from the coronavirus, ranges from 0.5% to 2.9% at the State level, with an average of 1.8% at the National level. This thesis is concerned with explaining those regional variations of COVID-19 deaths within the US and links regional mortality differences *ex post* to regional hospital capacity *ex ante* at the smallest administrative unit possible, the county level.

The Global Health Score (GHS) index ranked countries (in October of 2019) according to their preparedness for a global pandemic based on six different indicators. The supply of healthcare services was considered as an indicator, dubbed as a 'sufficient and robust health system', assessing health capacity, personnel, and equipment (GHS Index, 2019, p. 20). With the ongoing pandemic, analysing the supply side of healthcare services is more relevant than ever. Substantial academic progress has been achieved on the relationship between healthcare supply and variations in deaths. Several papers have found negative associations of regional variations in mortality with hospital bed supply (total and/or intensive care), the number of available medical personnel and healthcare expenditures. Yet, empirical supply-side models are often narrowly defined (e.g., intensive care units are the sole control variable of supply). As infected patients may require different healthcare services, based on the severity of their symptoms, a broader healthcare supply model is adopted to explain regional variations in covid mortality. The main model includes total, staffed and intensive care bed supply, medical personnel, healthcare expenditures and ventilator usage of regional healthcare. Additional supply-side control variables used are the type, ownership, and quality of hospitals in American counties.

By doing so, it is possible to gain insight into the relationship of regional pandemic health outcomes *ex-post* and the detailed dimension of supply *ex-ante*. Additionally, flattening the curve can be framed as a cost-benefit decision (Thunstrom et al, 2020, p. 1). Examining this relationship can clarify to what extent benefits result from investing in healthcare services *ex-ante*. This is both relevant to economists and policymakers since the ultimate economic costs of this pandemic will have a considerable effect. Accessing the relationship of deaths given the pre-existing supply of healthcare can help understand the associated benefits of investing in health care services.

Before analysing COVID-19 related mortality in the United States, it is necessary to look through an epidemiologist's lens to understand the current events. Firstly, I describe how pandemics may arise and what their merits are in general. Secondly, COVID-19 its features and causes are examined in more detail, and how the current pandemic fits into the overall pandemic scheme. This should suffice in giving the reader an overview from a medical perspective. After this overview, this framework focuses on COVID-19 medical and socioeconomic mortality covariates and, finally on healthcare within the United States. The remaining sections describe the dataset, methodology and outcomes including a robustness analysis of the supply-side model.

II - Theoretical framework

Pandemics

The WHO defines a pandemic as *'the worldwide spread of a new disease'* (WHO, 2020b). The definition of worldwide is if at least two different countries within a continent and one country from a different continent have known cases. As the WHO is the leading organization in global health, and advises governments on various health-related matters, it defined a phase description of pandemics and subsequent recommendations for *influenza pandemics* (WHO, 2020c). An influenza virus is an overarching term for contagious viruses that infect the nose, throat, and lungs, of which flu is an example (CDC, 2020a). Influenza typically circulates amongst animals and may or may not be transmittable to humans. Once influenza is capable of infecting humans locally, an *outbreak* occurs in a local community. Then, if the virus further spreads through local or regional communities, this refers to an epidemic (CDC, 2020b). Figure 1 portrays the gradience of an influenza pandemic as described by the WHO. Interestingly, influenza may develop into a seasonal disease post its peak, which is similar to the flu.

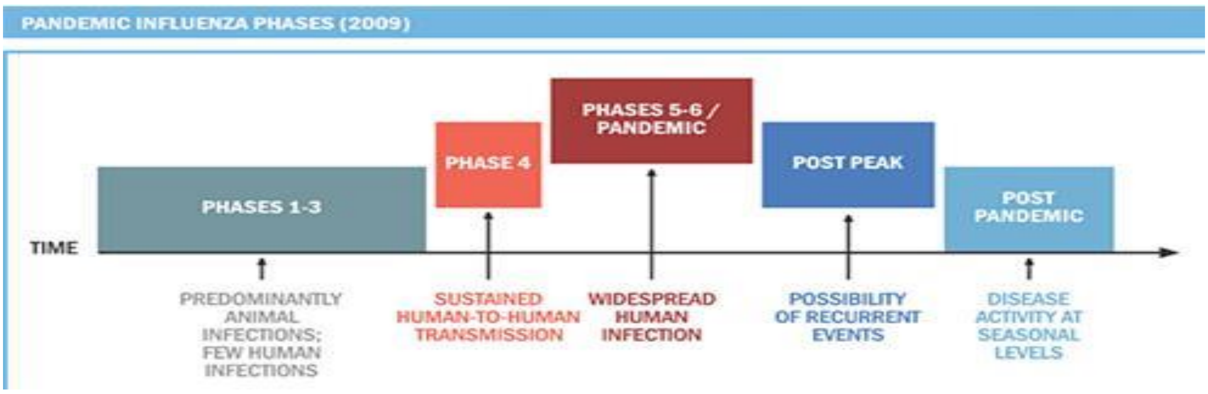

Figure 1: Phases of an influenza pandemic.
Source: WHO, 2020c

Morens, Kolkers & Fauci (2009) highlight additional components of pandemics: the severity, contagiousness, and minimal population immunity. Opposed to the WHO, the CDC incorporates severity and transmissibility (the reproduction rate *R*) in its Pandemic Framework (CDC, 2016a). Although the exact definition (as is often in science) of a pandemic may be debated, most definitions agree that a pandemic happens at a global scale and affects several countries or continents.

Historically, pandemics are rare but recurring events. The most known pandemic is the Plague (the Black Death) in medieval Europe, which recurred incidentally for 300 years (Stenseth et al, 2008), with the London and Italian plague as the most notable events. Bacteria spread from rats to humans via infected fleas and wiped out 30-50% of Europe's population with 200 million causalities (LePan, 2021). Interestingly, most early pandemics were caused by bacteria in rats or water (Cholera). Most pandemics in more recent times are caused by new influenza viruses. A hundred years ago, the Spanish flu pandemic had an estimated death toll of 40-50 million (LePan, 2021). The same type of H1N1 virus recurred one hundred years later, known as the Swine Flu. The SARS coronavirus, a similar virus to COVID-19, although with a lower death toll, was detected in 2002. The current pandemics are HIV/AIDS and COVID-19.

Table 1: Overview of several pandemics[1]

Name	Period	Cause	Death toll
Black Death	1347-1351	Bacteria from rats / Fleas	200M
Great Plague of London	1665	Bacteria from rats / Fleas	100.000
Italian Plague	1629-1631	Bacteria from rats / Fleas	1M
Cholera Pandemics 1-6	1817-1923	Cholera Bacteria	1M+
Yellow Fever	Late 1800	Virus / Mosquitoes	100.000-150.000
Spanish Flu	1918-1919	H1N1 Virus / Pigs	40-50M
HIV/AIDS	1918-present	Virus / Chimpanzees	25-35M
Swine Flu	2009-2010	H1N1 Virus / Pigs	200.000
SARS	2002-2003	Coronavirus / Bats	770
Ebola	2014-2016	Ebolavirus	11.000
COVID-19	2019-present	Coronavirus	2.5M+

Epidemiologists have several tools at their disposal to analyse historic and current pandemics. The most relevant are their knowledge of diseases and modelling their outcomes, such as the spread and death toll (CDC, 2016b). A major modelled determinant is contagiousness, known as the reproduction ratio *R*, which measures the average number of secondary cases per primary case (Boelle et al, 2009). If the overall $R > 1$, this means that an epidemic will occur, since infections will grow over time. If the ratio is smaller than one, the disease will fade out over time (Nikbakht et al, 2019). Most epidemics grow approximately exponentially during the initial phase of the outbreak. This means that the relationship between the number of infected or deaths is linear to a unit of time (log-linear) (Ma, 2020). The logistic model is not the sole model to provide an insight into contagiousness, but several models are used to analyse the (future) behaviour of the disease.

[1] Redacted, see full table at: https://www.visualcapitalist.com/history-of-pandemics-deadliest/

Ultimately, differences in *R* are an indicator of why an outbreak may result in a pandemic and its subsequent death toll. However, not all diseases lead to mortality. For instance, a reported 60 million American people were infected during the Swine Flu pandemic (2009), yet 0.02% of those cases resulted in death (Ricardson, 2020). Nevertheless, the Black Death in medieval Europe had a case-fatality ratio of 30% to 60% (Maassen, 2020), so mortality greatly varies in pandemics. Diseases may differ in contagiousness and mortality rate, yet most pandemics had a significant death toll. The usual timeline of a pandemic features 1) a local outbreak of a new disease transmitted via animals to humans 2) an epidemic due to a high level of contagiousness (*R* >1) and 3) simultaneous infections at the global level.

COVID-19

COVID-19, officially named SARS-CoV-2, is the disease stemming from a new coronavirus, that first appeared in December 2019 in Wuhan, China (Sauer, 2021). The virus is spread through human-to-human transmission by droplets (RIVM, 2021), officially called respiratory droplets (CDC, 2020d). A respiratory droplet is only contagious if it contains a certain amount of viral load (Kawasuki et al, 2020) and this viral load differs for each infected human (Maassen, 2021). Humans produce respiratory droplets in several manners, but most commonly by breathing, coughing, singing, and sneezing (CDC, 2020d). The virus can then spread in three different ways: contact transmission (contact with infected person or surface), droplet transmission (near an infected person) and airborne transmission (droplets in the air over longer distances) (Medicine, 2020).

The most common symptoms of COVID-19 are fever, dry cough, and fatigue. However, more severe symptoms may also arise including shortness of breath, persistent pressure in the chest, confusion, and high body temperatures (WHO, 2020d). In the United States, it is advised to seek emergency medical care immediately if someone is showing those severe symptoms (CDC, 2020d). Overall, the WHO states that about 80% of infected people recover without requiring hospital treatment. For the remaining 20%, 3 out of 4 require oxygen treatment and 1 out 4 need intensive care (WHO, 2020d).

As of March 11th 2020, the WHO declared SARS-CoV-2 a pandemic (Cucinotta & Vanelli, 2020). The outbreak had alarming levels of spread and severity, with a global number of 118319 cases and 4292 deaths (WHO, 2020). The new coronavirus spread in Wuhan (an outbreak), affected multiple communities in China (an epidemic) and ultimately affected almost every country and continent globally (a pandemic). Furthermore, the overall reproduction ratio (*R*) of COVID-19 was estimated at around 3 without any control measures and its case-fatality ratio (CFR) in the range of 2,5-2,75% (Yadav & Yadav, 2020). A feature of pandemics is generally a high reproduction value and usually a high death toll, which COVID-19 is capable of.

When comparing the current pandemic to pandemics in the past, it may seem that COVID-19 is severely less deadly than other novel diseases. Nevertheless, it is an insidious virus due to its high levels of contagiousness. For instance, the Ebola virus transmits via blood or body fluids (CDC, 2021), whereas COVID-19 can spread in three different manners (contact, droplet, and airborne transmission). Additionally, the overall reproduction ratio (*R*) of Ebola was estimated at 1.5-2.5 in West Africa (Althaus, 2014), which is also considerably lower than COVID-19 *R* of 3.

Table 2 sets out a simple comparison of the case-fatality ratio and reproduction ratio of the selected pandemics in Table 1. The case-fatality ratio is a measure that depicts the percentage of deaths of infected humans. As my knowledge of medicine is limited, I do not intend to explain variations in case-fatality rates of the selected pandemics. Nonetheless, symptoms of the disease, medicinal recourses and healthcare have a great influence on this outcome. Note that these variables are subject to how they are measured. This means that the time frame of the pandemic, the region and general assumptions may alter both the case-fatality ratio and reproduction rate. COVID-19 can be characterized as a relatively contagious novel disease, as yellow fever is the only pandemic that had a higher R. Regarding the case-fatality ratio, COVID-19 is somewhat less deadly than the average pandemic. As of March 17th 2021, the total number of recorded coronavirus cases is 121.5 million with around 2.6 million deaths, which is a case fatality ratio of 2.2% (Worldometer, 2021a).

The case-fatality ratio of COVID-19 depicts which percentage of known infected people ultimately die from contracting SARS-CoV-2, which is 2.2% on average globally (with an estimated 2.5%-2.75% in March 2020). Besides time variation, regional differences can vary greatly. For instance, the case fatality ratio is 4.8% in China, 2.9% in the United Kingdom and 1.1% in New Zealand (Jhon Hopkins University, 2021). And even within the same country, COVID-19 related mortality may differ. The average mortality rate in the United States is around 1.8%. Nevertheless, the mortality rate differs widely across states. Vermont, for instance, has the lowest mortality rate with 1.3%, whereas New Jersey, it's neighbouring state, has the highest with 2.8% (Worldometer, 2021c) What factors can explain *ex-ante* how a 1.5 percentage point difference in case fatality arises between two states *ex-post*? In other words: what are determinants of mortality from COVID-19?

Table 2: The Case-fatality ratio and reproduction rate of a selection of pandemics

Name	Death toll	CFR	Source	R	Source
Black Death	200M	30%-60%	Maassen, 2020	1.4-1.5	Sichone et al (2020)
Yellow Fever	100.000-150.000	20%-60%	Hamer (2018)	4.8	Lui & Rocklöv (2020)
Spanish Flu	40-50M	>2.5%	Taubenberger, & Morens (2006)	1.2-3.0	Vynnycky et al (2007)
Swine Flu	200.000	0.02%	Richardson (2020)	1.33	Furushima et al (2017).
SARS	770	11%	Moira & Rui-Heng (2003)	2.0-3.5	WHO (2003)
Ebola	11.000	50%	WHO (2021)	1.5-2.5	Althaus (2014)
COVID-19	2.5M+	2.2%	Worldometer, 2021a	3	Yadav & Yadav, 2020

Medical mortality covariates

Medical mortality covariates tend to account for factors that affect the outcome of a clinical trial (Segen's Medical Dictionary, 2011) implying the need to account for factors at the patient's level. The epidemic outbreak in Wuhan in early 2020 provided early data on possible medical mortality covariates of COVID-19 mortality (*comorbidities*). Caramelo et al (2020, p.8) estimated odd ratios of mortality based on age, gender, and common comorbidities of the Wuhan outbreak. Age is the most important predictor of dying: a patient of 80 years or older is 87 times more likely to die from COVID-19 than an individual who is younger than 80 (Caramelo et al, 2020, p. 8). A similar result was found by Michelozzi et al (2020, p.1) during the early outbreak in Italy, with excess in mortality (compared to the mortality rate pre-pandemic), which increased with age. Levin et al (2020, p. 1130) find an exponential relationship between age and deaths. And to put matters into perspective: 85+-year-olds have a 7900 times higher likelihood of dying to covid than a 5- to 17-year-old (CDC, 2020c). The measured CFR by age is increasing for each age group at the global scale (Worldometer, 2021a).

The stark evidence of age as a crucial determinant of mortality has been highlighted by many government agencies, academic and news articles, and politicians. Interestingly, gender also contributes to variations in mortality. Genderhealth50/50 (2021), a data-driven project tracking gender equality in global health, finds that males are relatively harder hit in terms of infections, hospital admissions and deaths. Michelozzi et al (2020. p.2) report higher excess mortality on average for males than females, which holds for every specified age group. Caramelo et al (2020, p.8) estimate that males are 1.85 times more likely to die from COVID-19 than females. Additional to age and gender, the role of comorbidities is assessed by several articles from medical journals, more commonly known as *underlying health issues* or *pre-existing health conditions*. Most articles use patients' data to delve into statistical relationships of health issues and COVID-19 mortality. Table 3 gives insight into a selection of common underlying health issues associated with an increase in regional deaths. Comorbidities are generally associated with a considerably increased risk of COVID-19 mortality and are very relevant for the effectiveness of COVID-19 related clinical trials.

Although some underlying health issues may be more of significance than others, health issues are an indicator of overall health. Even though overall health may decline due to age, which increases the risk of dying, an older individual is also more at risk of an underlying health issue. Age and comorbidities are therefore reinforcing, so the wide variety of medical academic articles provides an overwhelming amount of information on comorbidities. It proves it is additionally hard to assess all relevant health-related factors which play a role in a possible death of an infected individual. Nonetheless, one should at least try to account for such underlying health issues to properly analyse regional differences in deaths and this limited overview of comorbidities show the possible impact on mortality can be considerable on an aggregate level. To sum up: age, gender and comorbidities play a role in the overall mortality of COVID-19 and may explain regional variances from a clinical perspective.

Table 3: A selection of comorbidities associated with COVID-19 mortality.

Comorbidity	Effect	Source
Hypertension	Hypertension is associated with a 2.5x higher mortality risk	Lippi et al (2020)
Diabetes	Patients with diabetes are more at risk of rapid deterioration	Guo et al (2020)
Cardiac disease	Risk of mortality is 2.35x higher than non-cardiac patients	Inciardi et al (2020)
Chronic respiratory disease	A higher risk odd ratio of mortality	Caramelo et al (2020)
Cancer	Cancer is associated with higher all-cause COVID-19 mortality	Kuderer et al (2020)
Smoking	Current smokers have an increased likelihood of hospitalitation (1.8x)	Reddy et al (2020)
Obesity	Severe obesity increases the mortality rate up to fivefold for patients under 50 years old	Klang et al (2020)

Socioeconomic mortality covariates

Socioeconomic refers to a wide realm in which economic theory is applied in a social realm and links behaviour to social outcomes (Durlauf & Young, 2001), of which COVID-19 death may be such an outcome. Although general health and impediments of clinical trials may explain regional variances in covid mortality, several papers have analysed a wide range of socioeconomic mortality covariates related to regional differences in COVID-19 deaths, which include: demographic structure, meteorological variables, economic outcomes, inequality, modes of transportation, mobility, political stance, government policies and household characteristics (Allcot et al, 2020; Brown & Ravallion, 2020; Ding et al, 2020; Glaeser et al, 2020; Knittel & Ozaltun, 2020; Wu et al, 2020; Desmet & Wacziarg, 2021; Perone, 2021).

Knittel & Ozultan (2020) use a model of correlations to inspect the relationship between the regional death rates and US county-level characteristics. Although a model of correlations does not yield a causal result, the model confirms some basic findings from medicinal literature. The share of elderly, obesity and diabetics are positively correlated with the death rate (Knittel & Ozultan, 2020, p. 7). Brown & Ravallion (2020) use a maximum likelihood regression model, incorporating behavioural responses, to analyse excess mortality. Pre-existing health conditions have a weak effect (close to zero), although asthmatics and COPD have a weakly significant effect on death rates. Those effects tend to be weaker once more socio-economic covariates are included (Brown & Ravallion, p. 25). This shows that using medical mortality covariates associated with the effectiveness of a clinical trial (age, gender, comorbidities) cannot adequately explain regional differences of covid mortality without including socioeconomic controls.

Sannigrahi et al (2020, p .1) argue that demographic factors (total population, age, life expectancy) have a substantial impact on regional mortality differences in thirty-two European countries. Perone (2021) studied the impact of demographic factors in sixteen different Italian regions and found a similar result. A lot of academic attention is devoted to demographic structures and regional differences, albeit with a focus on racial disparities within the United States. Some papers report a positive correlation/association of deaths and the share of Black Americans within US Counties (Knittel & Ozultan 2020, Brown & Ravallion, 2020; Alcott et al, 2020; Wu et al, 2020). It shows that the socioeconomic context is highly relevant for the differences in mortality rates since the racial effect can be associated with a difference in social-economic status (SES). The Black community in the US is more often living in poverty, has lower education attainment and have overall worse health than the White communities (American Psychology Association, 2016).

Therefore, SES is an important indicator of explaining regional mortality differences. Brown & Ravallion (2020, p.27) excellently theorized how income and poverty jointly affect social distancing behaviour. Poorer families are likelier to have greater marginal costs of social distancing since these families cannot easily maintain their consumption level in isolation. Self-protective behaviour is a costly prospect for lower-income groups (Papagreorge et al, 2021, p. 716) and compliance to social distancing is lower in low-income neighbourhoods in New York City (Coven & Gupta, 2020, p. 1). These outcomes are often linked to the inability to telework (either by the nature of the job or not owning a computer at home) or using the cheaper public transit rather than own transport. Yet, one would expect that the median household income is negatively associated with covid mortality due to the ability to social distance. Desmet & Wacziarg (2021, p. 12) find this negative association, whereas Wu et al (2020, p. 12) report a positive association. Income inequality, measured by a Gini coefficient, is positively associated with mortality (Stojkoski et al, 2020). Empirical models are not unanimous on the effect of median household income and poverty.

Here, Brown & Ravallion (2020) note that the effect of income on the number of infections and deaths may vary, since income has a dual effect and should be analysed in conjunction with poverty. As discussed, a lower income decreases the possibility of social distancing, advocating a negative association of income with deaths. On the other hand, high-income families tend to have greater marginal costs to adjust to a lower level of social and economic interactions during a pandemic than low-income families (e.g. forgoing business trips, online meetings rather than physical). Which effect dominates when increasing income is not clear beforehand. Ultimately, Brown & Ravallion (2020) conclude that the joint effect of poverty and income is that both variables increase the number of expected cases, but the significance of poverty decreases when controlling for state fixed effects.

Poverty is also considered to be of lesser relevance in the model of Knittel (2020, p. 4), but poverty is described as a risk factor for COVID-19 mortality within these communities. Nonetheless, multiple reports describe how a lower median income and poverty decrease compliance with social distancing. Even though the exact relationship of a lower median income and higher poverty rate with mortality may vary in empirical models, most evidence regards these variables as mortality increasing. The same arguments apply to the unemployment rate: usually, a (weakly) positive association is estimated, but in some models, their role is negligible (e.g., Stojkoski et al, 2020).

As mentioned before, the SES comprises income, health, and educational attainment, of which the latter is not discussed yet. Most empirical models show that higher educational attainment yields a negative association with mortality (Desmet & Wacziarg, 2020). In academic literature it is often said that higher education is associated with better health and thus lower mortality

(Lynch, 2003, p 323). Additionally, workers with lower levels of education are less likely to work from home (Yasenov, 2020, p. 1), which is a disadvantage in a pandemic.

Some papers mention the relationship of meteorology with COVID-19 mortality, such as temperatures, humidity, and air pollution. Brandt et al (2020, p. 61) argue that relatively more dense populations see higher concentrations of air pollution based on New York City data. Comorbidities of COVID-19 are also somewhat linked to pollution. Zhu et al (2020, p. 5) also conclude air pollution is a relevant factor, based on data from the early pandemic in Wuhan, China. A rationale for affecting deaths is that air pollution may make citizens more susceptible to aerosols, the air transmission of COVID-19 (Van Doremalen et al, 2020). Ma et al (2020, p.6) find that absolute temperature and humidity are negatively associated with mortality. A similar result was found by Perone et al (2021) based on Italian data. The authors find that temperature is negatively associated with mean temperature and humidity. The rationale for this is that heat decreases the survival time of the respiratory droplets of the coronavirus on surfaces (Pawar et al, 2020), lowering the probability of transmission. Other noteworthy papers estimate positive associations of the use of public transportations (Knittel & Ozaltun, 2020; McLaren, 2020), less home ownership, average persons per household (Desmet & Waziarg, 2021) and regional mortality.

Socioeconomic mortality covariates provide information on possible relationships with regional covid mortality. Still, it should not give the impression that the number of deaths is a given based on medical and socioeconomic mortality covariates. Regional governments may influence the course of a pandemic with policies. Guzetta et al (2021) estimated that a two-week lockdown in Italy resulted in a reproduction value *R* below 1 for the next three weeks, using a Bayesian model approach comparing behavioural responses in a controlled intervention and an uncontrolled one (Guzetta et al, 2021). Liang et al (2020) find that governments that implement effective lockdown policies may reduce COVID-19 mortality significantly. Using the Oxford Government Response Tracker regarding implemented lockdown restrictions for 37 European Countries, Fullet et al (2021) estimate that a one-unit increase in the Stringency Index reduces mortality with 12.5 cumulative deaths per 100.000. The Stringency Index is a time-variant index comprised of 20 indicators regarding closure policies (e.g. closing schools), economic policies (e.g. income support) and health system policies (e.g. investments in healthcare), and together it records the strictness of national or regional lockdown policies (Hale et al, 2021).

Policies generally require a choice based on beliefs and therefore are politically sensitive, and the same applies to lockdown policies. Desmet & Wacziarg (2021, p.8) report an interesting pattern regarding Democratic and Republican US Counties based on Voting Data in the 2016 elections. Trump-leaning counties see a overall higher death toll in later stages of the pandemic, whereas Clinton-leaning counties did in the early stages due to population density. Republican voters are less likely to adopt social distancing measures (Alcottt et al, 2020) and hence the local conditions of Republican-leaning counties may worsen over time.

To give an overview of all relevant socioeconomic variables discussed in the literature, Table 4 sets out a comparison of variables and their association with COVID-19 related mortality. These control variables may differ in relative importance for an empirical model, yet it is only a description of the expected sign.

Table 4: Overview of socioeconomic variables and their association with COVID-19 related mortality.

Category	Variable	Association	Source(s)
Demographic Structure	Age (years)	Positive	Caramelo et al (2020)
	Gender (Male)	Positive	Michelozzi et al (2020)
	Race (Black)	Positive	Alcott et al (2020) Brown & Ravallion (2020) Knittel & Ozultan (2020) Wu et al (2020)
	Total population / Population density	Positive	Sannigrahi et al (2020)
Economical	Inequality (GINI)	Positive	Stojkoski et al (2020)
	Median income	Mixed	Brown & Ravallion (2020) Knittel & Ozultan (2020) Desmet & Wacziarg (2021)
	Poverty	Positive	Brown & Ravallion (2020)
	Unemployment	(Weakly) Positive	Stojkoski et al (2020)
Education	Educational attainment	Negative	Desmet & Wacziarg (2021)
Government policy	Stringency Index	Negative	Fullet et al (2021)
Health	Life expectancy	Negative	Sannigrahi et al (2020)
	Obesity	Positive	Knittel & Ozultan (2020)
	Pre-existing health conditions	(Weakly) Positive	Knittel & Ozultan (2020) Brown & Ravallion (2020)
	Smoking	Positive	Brown & Ravallion (2020)
Household	Home ownership	Negative	Desmet & Wacziarg (2021)
	Persons per household	Positive	Desmet & Wacziarg (2021)
Meteorology	Air pollution	Positive	Zhu et al (2020) Perone et al (2021)
	Humidity	Negative	Ma et al (2020)
	Temperature	Negative	Ma et al (2020) Perone et al (2021)
Transportation	Use of public transit	Positive	Knittel & Ozaltun (2020) McLaren (2020)

A crucial regional variation is yet to be discussed and requires a separate section, which is healthcare. To understand the interaction between healthcare supply and COVID-19 mortality, I first explain the dynamics of healthcare supply. In the last section, the American healthcare system is analysed in more depth to concretize features of American healthcare supply in a pandemic.

Healthcare supply in a pandemic

Healthcare resource availability has been one of the main arguments to implement lockdown policies. The rationale for a lockdown is straightforward: with a decline in the number of cases (lowering R), the total number of infections is lowered in the short term. The total number of COVID-19 cases should therefore decrease, guaranteeing the availability of healthcare resources. In March 2020, much emphasis was put on 'flattening the curve'. Almost all governments around the world took measures to spread out the number of infections over time, thereby reducing short-term demand for healthcare services (The Economist, 2020). Figure 2 entails an example of flattening the curve.

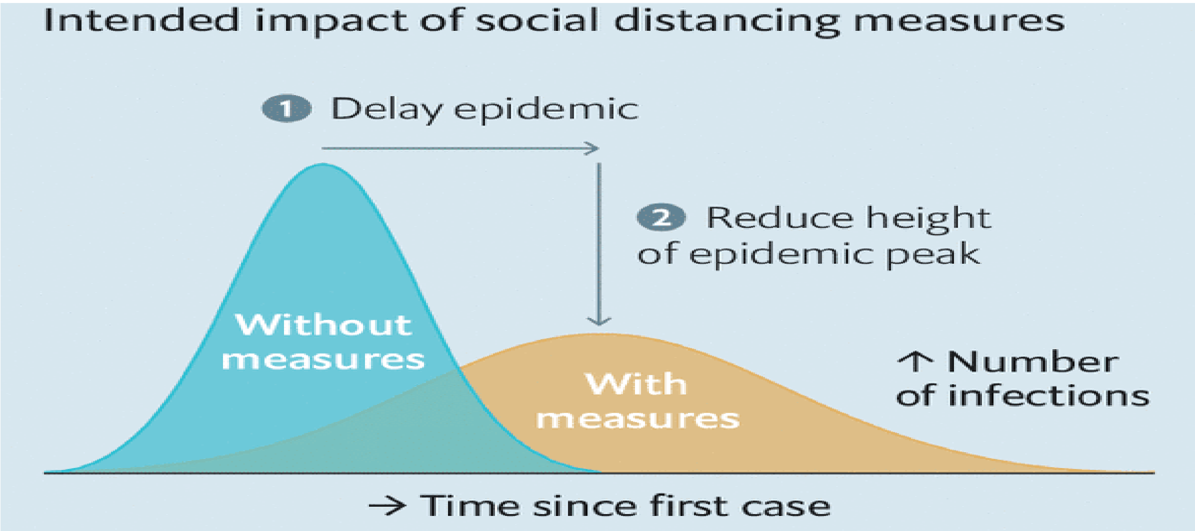

Figure 2: A visual representation of how lockdowns may affect the pandemic's peak.
Source: The Economist, 2020

The definition of the supply of healthcare services in a pandemic is not clear at first sight. Often, papers refer to healthcare capacity. The GHS Index (2019, p.99) defined medical personnel and hospital beds as health capacity when assessing the preparedness of countries for a pandemic (indicator 4.1). Bamford (2009) sums up some problems of healthcare capacity measurement (e.g. specification problems) and notes that capacity units are most often defined as bed capacity in the literature. Although it makes sense to view bed capacity as the main capacity unit in a pandemic, this definition is somewhat narrow. Hospital capacity planning involves several dimensions, including investments in facilities, equipment, and allocation of human resources (Ettelt, 2008, p.5). Furthermore, a healthcare system consists of different layers of national and regional actors, and national governments are usually the financers of healthcare.

Therefore, I use the definition of healthcare services of Ransom & Olsson (2017): healthcare services comprise of all materials, personnel, facilities, and funds that can be used for services, such as treating COVID-19 patients. I opt for this definition since it includes funds. Bonovas et al (2012) argued that the more severe recession in Greece, which hampered the ability to fund its healthcare, is a reason why a higher mortality rate was observed during the 2009 Swine Flu pandemic. Regarding to the treatment of a covid-infected patient, not all infected patients require medical treatment. And for those requiring treatment, these patients differ in demand for 'regular' or intensive care. For those patients requiring medical care, the treatment of one COVID-19 patient requires a hospital/ICU bed, protective equipment (e.g., ventilator, N95 masks) and trained personnel (Crowe et al, 2021, p. 57). Additionally, governments finance these necessities. Those components are what is understood as the supply of healthcare services for a COVID-19 infected patient. A hospital has a limited capacity to treat COVID-19 patients. The total number of patients a hospital can treat is defined by hospital capacity and at the national level, this is referred to as healthcare capacity.

Several features of healthcare supply during a pandemic should be mentioned. One feature of healthcare services is quality. Patients seek to improve their health and medical personnel optimizes its services given some medical or financial constraint. The higher the quality of healthcare services, the more likely health improvements occur. Healthcare quality is therefore associated with procedural mortality rates (Dimick et al, 2004). Secondly, adjusting the total healthcare supply takes time (e.g., personnel needs training, the building of ICU, purchasing protective equipment) to adjust and is therefore inflexible in the short term. The inflexibility of hospital capacity is best explained by Roemer's Law: hospitals are built where beds can be filled (Goodwin, 2011). Thirdly, a healthcare system can reallocate its capacity to meet short-term demand. Lefrant et al (2020) describe how France was able to double the number of physicians, ICU beds and ventilators to treat infected patients. However, this does not imply that healthcare capacity was doubled: medical personnel was reallocated and only 1 out of 8 added ICU beds was newly built. Reallocation implies that COVID-19 healthcare is prioritized while reducing capacity for other types of healthcare. Both in the US (Berlin et al, 2020) and UK (The Lancet Rheumatology, 2021), a significant backlog in non-emergency surgical procedures is reported because of reallocation.

The total demand for hospitalization consists of the demand for COVID-19 related hospitalizations and non-COVID-19 related demand. To see how a problem may arise, consider the following example. In Lombardy (Italy), 85% to 90% of the ICU beds are on average occupied for 'regular' care in the winter in pre-pandemic years (Manca et al, 2020). This would imply that a maximum of 85 ICU beds is available for patients infected by covid in that period. Assuming a 5% ICU rate, the demand for ICU beds would exceed hospital capacity if the total number of active cases in Lombardy is above 1.700. With a total number of 700.000 cases in the Lombardy region in a year (New York Times, 2021), averaging more than 1.700 *new active* cases every day, one can easily see why healthcare capacity should be reallocated during a pandemic.

Fisher et al (1994) note that physicians consider to what extent hospital resources are available when referring patients, therefore a physicians' clinical decision resembles a threshold function related to hospital capacity. In non-pandemic times, physicians would act as an agent managing and prioritizing healthcare capacity. If hospital beds are scarce, then physicians are reluctant when referring a patient to a hospital. The events of the pandemic would only reinforce this principle, meaning that both hospitals (directly) and physicians (indirectly) prioritize COVID-19 related healthcare.

Concluding, healthcare capacity has a two-fold constraint in a pandemic: i) the supply of services it can offer to COVID-patients and ii) the remaining supply of regular healthcare services. Since physicians act accordingly to the availability of healthcare resources, a government is effective in prioritizing the type of supply of healthcare services, but at the expense of the healthcare services that have to be deprioritized.

Several papers have assessed the pressure on (regional) healthcare capacity in the surge of a pandemic by (micro-)simulation models. For instance, Ferstad et al (2020, p. 9) estimated in March 2020, that twenty US Counties would see a 500% or higher utilization of ICU beds if 1% of the total regional population would have COVID-19 related symptoms. Murray (2020, p.7) forecasted that during the peak of the pandemic, there is an excess demand of 9359 ICU beds (above healthcare capacity) and that excess demand would occur for circa 6 weeks in the US.

Not being able to treat infected patients, or needing to lower standards of care, may result in a higher number of COVID-19 related deaths (Miller et al, 2020, p. 1212). However, it is not clear cut whether a higher supply of healthcare services *leads* to lower mortality levels. A cross-sectional study from Crowe et al (2021) finds a positive association between the number of ICU beds per 100.000 and COVID-19 deaths. The authors state that population density seems to be the main driver of deaths, controlling for a higher number of ICU beds that can be found in more populated areas. Knittel & Ozultan (2020) find a non-significant correlation between the number of ICU beds and covid mortality, arguing that the supply is not what matters most. This model controls for some comorbidities, race, age, temperature, and poverty.

However, I suspect those models are driven by two methodological issues. Firstly, an OLS regression analysis with the number of deaths and ICU beds would likely suffer from an omitted variable bias. Since these two variables are positively correlated, a naïve regression would report a positive sign. Secondly, only assessing the number of ICU beds does not fully capture healthcare supply in a pandemic. As short-term supply is inflexible but can be reallocated, the number of actual ICU beds is underreported in the data. Including the total number of hospital beds, pre-pandemic would therefore more adequately capture the correlation between ICU beds and mortality to account for unobservable reallocation.

Most academic papers do report a negative association of healthcare supply (most commonly the number of beds) and mortality with different type of approaches (Total Deaths, CFR and Excess Mortality). Looking at Table 5, a vast number of papers find a negative relationship between the number of ICU/Hospital beds and either total COVID-19 deaths, excess mortality, or the CFR. In some models, the number of beds is not of significance. However, almost all papers fail to capture the full healthcare supply in their models. One model comes close to this paper's definition of healthcare supply during a pandemic. Perone et al (2021) include healthcare expenditures and medical personnel in an OLS model to estimate the association of hospital beds on the CFR. Nonetheless, supply is still not adequately captured. The number of ventilators is also an important denominator, which only Moreira (2020) includes in its mortality regression model. This gap in this research has, to my knowledge, not been filled yet. Therefore, this gives rise to the necessity of a socioeconomic model which includes all the supply side's relevant components (all materials, personnel, facilities, and funds).

Table 5: An overview of academic literature on the relationship of healthcare supply and a measure of COVID-19 mortality.

Supply Variable	Approach	Variable of interest	Result	Source	Data
Healthcare expenditures	Cross-sectional OLS regression	CFR	Negative association	Bonovas (2012)	European Countries
Healthcare expenditures	Cross-sectional OLS regression	CFR	Positive association	Perone et al (2021)	Italy (Provinces)
Healthcare expenditures	Cross-sectional OLS regression	CFR	Negative association	Sorci et al (2020)	European Countries
Healthcare expenditures	Bayesian model ranking 31 variables	COVID-19 deaths	Significant impact (3^{th} out of 31)	Stojkoski et al (2020)	106 Countries
Hospital beds	Cross-sectional OLS regression	CFR	Negative association	Ergönül et al (2021)	34 Countries
Hospital beds	Correlation model	CFR	Negative association	Lansiaux et al (2020)	France
Hospital beds	Cross-sectional OLS regression	CFR	Negative association	Liang et al (2020)	169 Countries
Hospital beds	Cross-sectional OLS regression	CFR	Negative association	Perone et al (2021)	Italy (Provinces)
Hospital beds	Cross-sectional OLS regression	CFR	Negative association	Sorci et al (2020)	European Countries
Hospital beds	Correlation model	COVID-19 deaths	Negative association	Hradsky (2021)	210 Countries
Hospital resource availability index	Bayesian model ranking 31 variables	COVID-19 deaths	Average impact (16^{th} out of 31)	Stojkoski et al (2020)	106 Countries
ICU and non-ICU bed usage % of bed capacity	Estimation model	COVID-19 deaths	Negative association	Karaca-Mandi et al (2020)	US (States)
ICU beds	Correlation model	CFR	No significant relationship	Knittel & Ozaltun (2020)	US (Counties)
ICU beds	Cohort study	Covid Deaths	Positive association	Bravata et al (2021)	US (Veteran Hospitals)
ICU beds	Demand model to estimate shortage of critical care bed supply	Excess Mortality	12.203-19.594 excess deaths in four weeks	Branas et al (2020)	US (Counties)
ICU beds	Cross sectional spatial model	Excess Mortality	Positive association	Moreira (2020)	Brazil (Provinces)
ICU beds	Time series	Excess Mortality	40% of Excess Mortality is due to COVID-19	Sjödin et al (2020)	Sweden (Provinces)
ICU beds and acute care beds	Cross-sectional OLS regression	Deaths per 100.000 population	Positive association	Crowe et al (2021)	183 countries
ICU beds per 1000	Predictive model	CFR	No significant relationship	Malki et al (2020)	Italy (Provinces)
Medical personnel	Cross-sectional OLS regression	CFR	Negative association	Ergönül et al (2021)	34 Countries
Medical personnel	Pearson Test	CFR	Negative association	Lansiaux et al (2020)	France (Provinces)
Medical personnel	Cross-sectional OLS regression	CFR	Negative association	Perone et al (2021)	Italy (Provinces)
Ventilators	Cross sectional spatial model	Excess Mortality	Negative association	Moreira (2020)	Brazil (Provinces)

American Healthcare in the pandemic

In 2018, the US contained more than 919.539 hospital beds and 131.564 intensive care beds, which are spread out over more than 6090 hospitals. There are 5141 community hospitals, of which 24% is a private for-profit, 57% is a private non-profit, and 19% is a government organization (AHA,2021). American society spent on average $11.072 per capita on healthcare of which $1,150 is out of pocket expenses in 2019 (OECD, 2019). Contrary to most European Healthcare models, American healthcare is most known for its private healthcare market and a lack of a compulsory insurance scheme. The US does have a national health insurance programme named Medicare (for the elderly) and a programme for Veteran Aid. In the first half of 2020, around 31 million Americans did not have health insurance, which is around 10.5% of all adults (Adavelli, 2021). In most cases, the employer pays for its employees' health insurance, but this varies due to differences in State law.

Americans may face medical expenses if hospital treatment due to a covid infection is required. FairHealth (2021) estimates these costs at $73.300 for an uninsured individual or an insured individual who received hospital treatment outside of the insurance company's network. Even insured individuals may face costs due to deductibles. Many empirical models, based on US Counties data, therefore included the rate of uninsured adults as an explanatory variable. Health insurance is also associated with a better Social Economic Status (SES). The US is also known for its large SES-inequalities, based on race, region, and age. And as was discussed before, these factors may impact COVID-19 mortality apart from the financial ability to seek medical treatment.

Turning to the events of the pandemic in the US, there have been over 30.6 million infections and 556.000 deaths, a CFR of 1.8% (Worldometers, 2021c). It has been the country which is affected the most over of a year. At the beginning of the pandemic (spring 2020), New York City was the epicentre of the novel coronavirus in the US, and it was also one of the most densely populated areas (Alcott et al, 2020). Various states had to make emergency adjustments to their healthcare later. As of 2021, Los Angeles is the worst off and the State of California has recorded the highest number of covid deaths in March 2021 (Worldometers, 2021c).

Why the US has one of the highest covid deaths per capita, is a difficult question to answer. Nonetheless, some American issues, which are likely to affect the course of a pandemic, are worth mentioning. Firstly, States can enact lockdown (related) policies, but lockdown policies are also politically sensitive. Republicans and Democrats differ in their willingness to adhere to social distancing measures (Alcott et al, 2020), so elected governors may enact different social distancing policies (or not at all).

Secondly, the Federal US government implemented relatively smaller stimulus packages than other developed nations, worth 14% of its GDP in 2019 (Buchholz, 2020). Hence, several economic developments occurred as the US has lower socials security standards and had smaller stimulus packages (compared to the EU). In April 2020, the unemployment rate rose from 4.4% to 14.7%. However, the current unemployment rate is 6% (FRED, 2021). Being unemployed may affect an individual's health insurance and financial ability to seek medical treatment. Additionally, 41 million Americans were at risk of being evicted in 2020 (CBS News, 2020). Being evicted may affect an individual's health and deprives individuals of a place to safely self-isolate. Also, States differ in laws preventing evictions and utility shutoffs (O'Connell, 2021).

Lastly, US hospitals were faced with a shortage of ventilators from March to April in 2020, and the problem was related to the global supply chain (Iyengar et al, 2020). Most countries faced this ventilator shortage and had to divide the existing and new stock. However, all States bought a new stock of ventilators separately on the market. Since ventilators were scarce, this meant that States enacted in a bidding war. Ventilators were thus not divided from the federal level to the State level according to a necessity principle, but the States with the highest willingness to pay received the first supplies. Whether this affects regional deaths positively or negatively is not clear (since the willingness to pay would increase with necessity), yet it is a feature of the American healthcare system that should be mentioned.

Even though the pandemic still yields considerable problems in the US, vaccines are considered the solution. The US started vaccinating on the 14th of December 2020 (BBC, 2020). As of March 19th, 2021, 100 million vaccine shots were administered in the US (NYTimes, 2021). At least 1 out of 8 American adults is now fully vaccinated, with 1 out of 4 having received the first shot (CDC, 2021). Being immune to the coronavirus reduces the overall number of cases and ultimately mortality. The focus is therefore now on reducing overall mortality, instead of managing it, and lifting lockdown policies gradually.

III - Data

I use daily data on the number of COVID-19 cases, deaths at the county-level[2], total vaccinations[3] and lockdown policies at the state level[4] (since there is no county-level dataset available). The data period is 21-01-2020 until 20-3-2021, except for the vaccine data, as the US started vaccinating on December 14th, 2020. The first dataset consists of daily data on the number of cases and deaths in US Counties provided by the New York Times. Lockdown policies are implemented by either the Federal, State, or sub-State governments and may differ. The Oxford University excellently maps the daily variations in State Policy Responses based on economic, social distancing and health policies. It provides for a Stringency Index: an overall measure of how strict States respond at a given date. This measure does not reflect effectiveness, but merely the behaviour of government policy over time. Together with daily vaccine data at the State level, the main developments in the US pandemic can be accurately tracked daily. The CDC has a county level vaccination database, but has, unfortunately, not published it for the public yet, therefore state-data is used.

As this paper analyses how the supply of healthcare services is related to regional differences in deaths, several hospital datasets are used. The dataset of Definitive Healthcare[5] provides the most extensive dataset of 6,629 hospitals in the US. This number is higher than mentioned before since it includes Children, Religious and Veteran hospitals (~300 hospitals). It includes several supply-related variables: ICU beds, total hospital beds, staffed beds, average bed utilization, average ventilator usage and potential bed capacity increase (measured as the difference in normal and ICU beds). Unfortunately, this data is not a time series and has no time variation in hospital capacity, but hospital information was updated regularly (the exact update date is unknown to the public).

[2] The New York Times, 2021 https://github.com/nytimes/covid-19-data.
[3] OurWorldInData, 2021 https://covid.ourworldindata.org/data/vaccinations/us_state_vaccinations.csv
[4] Hale et al, 2021 https://github.com/OxCGRT/USA-covid-policy
[5] ESRI, 2021 https://coronavirus-resources.esri.com/datasets/definitivehc::definitive-healthcare-usa-hospital-beds?geometry=-99.492%2C-16.820%2C74.531%2C72.123

The project started in 2016, so the data period of this data is 2016-2020. To elaborate on hospital information, a dataset (2017) on the features and quality of Medicare registered hospitals are linked[6], including the type of hospitals, ownership (public, private, government) and overall quality measures (e.g. mortality, effectiveness). Albeit the data is from 2017, it comprises detailed information at the hospital level. For instance, the CMS has rated hospitals on a 1-5 scale to provide quality information to healthcare patients. Furthermore, it compared mortality, patient experiences, readmission rate and effectiveness, safety, timeliness of care of those hospitals with the national average. All things considered, there are detailed quality dimensions present in the data and therefore an asset for analysis. The literature has analysed the relationship between hospital beds and COVID-19 mortality in several manners; to add relevance to the literature, I use detailed data on hospital supply information at the expense of recent quality data and some hospital bed data (yet most papers use 2019 bed data). As the quality of healthcare may be related to procedural mortality rates, and therefore the number of deaths, this is also a supply dimension that is not covered yet by the literature. It also allows for differentiating between the type of hospital beds. Not all covid infected patients require intensive care treatment, so a distinction is necessary between normal and ICU beds.

The pandemic sparked many data scientists to put together extensive datasets, one of which contains a wide set of socioeconomic and health-related outcomes at the county-level[7]. Data has been pooled from CDC Social Vulnerability Data (2016), Community Health Rankings Data (2020) and Weather data (2020). It provides for many socioeconomic covariates, but also the number of patients a physician treats on average within a county. Merged with data on healthcare expenditures at the state level[8], I believe that a broad scope of supply features is captured in the data. The socioeconomic covariates are extensive (e.g. mental distress, physical exercise, access to healthcare, segregation). It explores health-, healthcare-, socioeconomic-, housing-, meteorological-, demographic- and commute-related outcomes. Nevertheless, additional control variables are added to this dataset. Firstly, I use a county level dataset of the Economic Research Service of the US Department of Agriculture based on 2019 data (USDA)[9]. This includes the Social Economic Status (SES), based on poverty, unemployment, median household income and education. Lastly, this is pooled with data on the voting behaviour of county citizens in the 2016 and 2020 Presidential elections[10]. An overview of the data can be found in Table 6.

The construction of this county dataset has two main advantages. Firstly, it features detailed information at the county level in multiple manners. It is inspired by what the literature has found today on various socioeconomic relationships with COVID-19 mortality, yet it is more detailed than the data that is used in other papers. Secondly, the supply-side dimension is an addition. Although some papers have included supply-side elements such as the division in hospital beds, or healthcare expenditures, this data can shed light on the interaction of supply-side elements with the regional differences in deaths more extensively. This construction comes also at the expense of

[6] Centers for Medicare & Medicaid Services,2017 https://www.kaggle.com/cms/hospital-general-information
[7] Davis, 2020 https://www.kaggle.com/johnjdavisiv/us-counties-covid19-weather-sociohealth-data
[8] CMS (2017), https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsStateHealthAccountsProvider
[9] USDA, 2019 https://www.ers.usda.gov/data-products/county-level-data-sets
[10] Schacht (2020) https://www.kaggle.com/etsc9287/2020-general-election-polls

the recency of the data in some cases. However, this applies to health-related outcomes mainly. The ESRI Hospital dataset is updated regularly, so it can be assumed that hospital information is not outdated.

Table 6: Overview of variables in the dataset

Category	Variable	Level	Period	Source
COVID-19	Cases*	County	2020-2021	NYTimes (2021)
	Deaths*	County	2020-2021	NYTimes (2021)
	Lockdown*	State	2020-2021	Hale et al (2021)
	Vaccines*	State	2020-2021	OurWorldInData (2021)
Healthcare supply	Physicians	County	2020	Davis (2020)
	Hospitals	County	2016-2021	ESRI (2021)
	Healthcare expenditures	State	2020	
	Quality of hospitals	County	2017	CDC (2017)
	Hospital beds	County	2016-2021	ESRI (2021)
	Ventilator usage	County	2020	ESRI (2021)
Socioeconomic & Medical mortality covariates	Demographics	County	2020	Davis (2020)
	Socioeconomic status	County	2019	Davis (2020)
	Meteorology	County	2020	Davis (2020)
	Health related	County	2016/2020	Davis (2020)
	Voting behaviour	County	2020	Schacht (2020)

*Variables denoted with * are timeseries (unit: daily), the remaining variables are structural.*

The merge of several public datasets had an insurmountable loss of data for different reasons. Firstly, 1% of the New York Times county dataset consisted of unidentifiable counties. Secondly, data was pooled on a unique identifier of state and county name denoted by FIPS (federal information processing standards) code. Not all datasets had a FIPS-identifier, so much attention has been devoted to ensuring data entries had this identifier. Thirdly, New York City COVID-19 data is tabulated at the city level, instead of divided over the five counties. Therefore, some statistics were mean-weighted based on population share. Overall, 99% of the data on cases, deaths, vaccinations, lockdown policies and main supply variables are maintained. Missing supply variables are only set to 0 when this fits within the context (number of hospitals, personnel, beds etc), but a loss of data is inevitable when using a wide set of control variables (up to 30%) and/or additional supply-side control variables conditional on having at least one hospital in a county (e.g. quality of hospitals, up to 10%). Therefore, a trade-off exists within this panel dataset.

As stated before, the number of COVID-19 deaths may differ regionally. New York has the highest death toll with 48916 deaths and Vermont the fewest with 219. Massachusetts is the State that is relatively hit hardest, with an average CFR of 2.9%. In comparison, Utah has a CFR of 0.5%. The national average is 1.8%, the same as found in the statistics of international covid trackers. The number of cases and deaths differs slightly from the current figures on March 20th 2021 (around 1 million cases and 30.000 deaths), but this would be due to lost data and is not expected to be of major influence. Table A1 provides descriptive statistics on the supply side of hospital services during a pandemic. For each county, several variables were derived: the total number and type of hospitals, various types of hospital beds and medical resources (ventilators, patient per physician and expenditures). Additionally, quality indicators of hospitals on a 1 to 5 scale are included. On average, 323 total hospital beds are available for patients with 31 of those being ICU beds. ESRI defined the potential capacity of hospitals as the difference in all hospital beds and ICU beds, so this variable measures the capacity to meet short term demand in a pandemic. Twenty-one per cent of the Counties did not have a hospital. Since COVID-19 data of New York City is tabulated at the city level, instead of divided over the five counties, New York City is the absolute leader in healthcare supply with 106 hospitals and 23854 hospital beds. Table A2-A5 report descriptive statistics on the main supply, quality, medical- and socioeconomic mortality covariates.

IV - Methodology

The goal of this paper is to adequately capture the interaction of the supply side of healthcare services in a pandemic and deaths of COVID-19. The CFR can be easily estimated by dividing the cumulative number of confirmed COVID-19 deaths (X) by the cumulative number of lab-tested COVID-19 cases over time (t) within a region (r).

$$CFR_r = \frac{\sum_{i=t}^{n} X_{rt} + X_{rt+1} + X_{rt+2} + \cdots + X_{rn}}{\sum_{i=t}^{n} C_{rt} + C_{rt+1} + C_{rt+2} + \cdots + C_{rn}} = \frac{X_r}{C_r} \tag{1}$$

The CFR is therefore relatively straightforward: the higher the number of deaths given an exogenous number of cases, the higher the CFR is and vice versa. Supply of healthcare services is defined as all material, personnel, facilities, and funds that can be used for providing COVID-19 treatment. The supply side of health care services is inflexible in the short term; meaning some capacity exists at a given time, assuming that there is no or little additional supply after capacity is reached. Specifically, a patient requires a hospital/ICU bed, medical assistance and a ventilator if needed. Those three components are jointly the medical service. The capacity of the supply side of healthcare services in a pandemic is some minimum function related to these components since either may be a capacity constraint.

$$\bar{S} = min\{\mathrm{B}, \mathrm{P}, \mathrm{V}\} \tag{2}$$

The demand for (regional) healthcare services is forecasted in many epidemiologist papers with complex equations. Here, a relatively simple demand equation is used based on the number of cases within a region. An infected individual may or may not require medical services based on the development of symptoms with probability η. If the patient's health deteriorates during the infection due to difficulty with breathing, he or she receives intensive care medical services. The WHO estimated that η=0.2 for general medical services and η=0.05 for intensive care treatment on average. However, η can vary for individuals and, therefore, at the regional level. So, the total demand for healthcare services at time t within a region can be denoted as a fraction of the total infected individuals at date t requiring medical services:

$$D_{rt} = \eta_{rt} * C_{rt} \tag{3}$$

To explore how regional covid deaths relate to healthcare supply, assume that the number of deaths can be computed by calculating the number of individuals who do not receive medical care (demand exceeds supply). Deaths would depend on supply by:

$$X_{rt} = D_{rt} - \bar{S_r} \tag{4}$$

It would be better to include the treatment effect of healthcare services on the total number of deaths (since some patients are treated but may die). Assume that death would still depend on the ability to provide treatment s, but the probability of a successful treatment is Ψ (patient survives) and a random probability of dying σ occurs. Then the equation reads:

$$\Pr(X_{rt}|s = 1) = \Psi_{rt} - \sigma_{rt} \tag{5}$$

$$X_{rt} = \eta_{rt} * C_{rt} - (\Psi_{rt} - \sigma_{rt})\bar{S_r} \tag{6}$$

$$\frac{X_{rt}}{C_{rt}} = \eta_{rt} - \frac{(\Psi_{rt} - \sigma_{rt})\bar{S_r}}{C_{rt}} \tag{7}$$

Equation (6) shows some basic features to be expected. Firstly, regional deaths increase if the probability of hospitalization is high (the covariate effect). Secondly, a higher treatment effect of supply decreases the expected number of deaths (the quality of supply effect). Thirdly, rewriting deaths to the CFR in equation (7) reveals that deaths decrease when a higher supply per infected (active cases) is achieved (relativity of supply effect). Although this equation is not a realistic scenario to estimate differences in regional deaths, a simple mathematical exercise does give insight into the three mechanisms of regional covid deaths and supply if deaths occur through excessive demand. Through these three mechanisms, differences in deaths can arise.

Drawing from these three mechanisms, I use a State Fixed Effect (FE) regression model to estimate the effect of regional supply on the regional deaths. As mentioned, the supply side consists of a wide dimension of covariates. To account for the effectiveness of healthcare, quality of hospital data is included in the regression model. The probability of hospitalization η_{rt} and total deaths X_{rt} are likely to be strongly related, so the regression model deploys a wide set of socioeconomic control variables to account for omitted variable bias (to counter overestimation of β). The control variables can be categorized in health, demographic, SES, political, policy and meteorology outcomes (η_{rt}). The number of cases is also included in the model, such that $\delta c_r + \omega p_{rt} + \varphi v_{st} + \pi C_{rt} \asymp \eta_{rt} * C_{rt}$.

As the number of deaths is a time-variant outcome variable partially based on the time-variant effects of i) overall infections C_{rt}, ii) preventing infections due to lockdown policies p_{rt} and iii) immunization of the population v_{st}, the model allows for lagged variables. The median number of days to die after a covid infection is 14 days (Wang et al, 2020), such that the standard lagged variable is 14 days. The same period applies to lockdown policies since the *R*-value is often measured after 14 days (Guzetta et al, 2021). Regarding immune population effects on deaths, the lag would depend on the administrated vaccine. Additionally, the administrated vaccines yield different levels of immunity before being fully immune after a possible first or second shot depending on the type of administrated vaccine. To overcome this unobservable variance, the fully vaccinated (either after the 1st or 2nd shot) per hundred at the state level are included. For the sake of simplicity, I assume that the effect of this shot is prevalent 14 days after administrating the last required shot. This vaccination rate v_{st} is 0 for all Counties before 14/12/2020.

Lastly, there are many unobservable differences between Counties. If the socio-economic control variables can solve this problem at the regional level, state-fixed effects λ_s may further limit this threat to the internal validity of the model.

The model reads:

$$X_{rt} = \alpha_r + \beta S_r + \delta c_r + \omega \mathrm{p}_{rt-14} + \varphi v_{st-14} + \pi C_{rt-14} + \lambda_s + \varepsilon_{rt} \tag{8}$$

X_{rt}	= the number of COVID-19 deaths at county level (r) at a given date (dd-mm-yyyy).
α_r	= a county varying constant
$\beta\overline{S_r}$	= regional supply
δc_r	= socioeconomic and medical mortality covariates at county level
$\omega \mathrm{p}_{rt-14}$	= social distancing policies at county level at a given date (day-month-year).
φv_{rt-14}	= fully vaccinated at State level at a given date.
πC_{rt-14}	= the number of cases at county level at a given date
λ_s	= State fixed effects
ε_{rt}	= County-time specific error term

V - Results

The supply side model

To understand how the supply model interacts with the number of regional deaths, Table A6 gives a selection of correlations of the main supply variables and the number of deaths. None of these supply indicators is negatively correlated with the number of deaths. Most strongly correlated are the factors of direct supply (beds, hospitals), except for the number of patients per physician. This is what should be expected: counties with more (direct) supply tend to have a higher population or a population with a high healthcare demand pre-covid. Both would lead to a higher number of expected deaths. It also highlights a threat to the internal validity of a model including supply as its explanatory variable, as selection bias may alter the sign of the coefficient of interest.

Turning to the supply model estimation, Table 7 sets out a basic OLS supply-side model without control variables with the number of regional deaths as the dependent variable. Since this model does not have any time variation, the model analyses between-county variance only. Suppressing time variation has a caveat, with the constant in the model able to account for a large share of the regional variance. Nonetheless, it provides for an intuition of the relationship between healthcare supply and regional covid mortality. Four model specifications are used, building up to the definition of the supply of healthcare services used in this paper (all materials, personnel, facilities, and funds).

In the first naïve model specification, hospital supply is defined in the narrowest definition: hospital beds, the use of those beds and the number of hospitals. Note that the adjusted R-squared is quite considerable in size, showing that some time variation is needed to analyse regional mortality. The hospital bed coefficient is positive, yet the use of beds is associated with mortality decreasing at a significance level of 0,1. Adopting a distinction in the total supply of beds (total hospital beds, hospital beds with staff and ICU beds in model 2) displays an interesting relationship. The total supply of hospital beds drops its significance. Although staffed beds have a positive sign, the ICU beds have a large negative significant coefficient for all model specifications.

Moreover, the supply of doctors and primary care workers is associated with a increase in the number of regional deaths (model 3): the more patients per medical personnel, the more deaths. As medical personnel can be overloaded with the treatment of infected patients simultaneously, one would expect this sign to be positive. Interestingly, the use of beds loses its significance when controlling for medical personnel supply. A rationale for including the use of beds is to account for possible healthcare pressure or scarcity of healthcare services. The number of beds that can be used is correlated to some extent (0.264, see Table A6) to the supply of medical personnel in hospitals and therefore the medical workforce can more adequately account for variances in healthcare pressure. Turning to the full supply model (4), circa 350 Counties do not have known state-level data of healthcare expenditures (funds). Funds are associated with mortality increasing, whereas the use of ventilators is decreasing (although not significant). As the model does not include any control variables, conclusions should not be drawn yet, but an intuition of further models can be derived from Table 7.

Table 7: Basic OLS supply side model without medical or socioeconomic mortality covariates

	(1) **Deaths**	(2) **Deaths**	(3) **Deaths**	(4) **Deaths**
Hospital beds	0.846***	0.213	0.244	0.253
	(0.327)	(0.424)	(0.419)	(0.422)
Staffed beds		1.392***	1.357***	1.365***
		(0.402)	(0.388)	(0.393)
ICU beds		-6.064**	-5.959**	-5.858**
		(2.885)	(2.816)	(2.741)
Average Beds utilized	-1.437*	-1.485**	-0.066	0.714
	(0.773)	(0.665)	(0.457)	(0.586)
Hospitals	-41.227	-39.935	-39.758	-44.537
	(56.903)	(41.347)	(40.510)	(43.958)
Patient per physician			-1.231***	-1.119***
			(0.362)	(0.283)
Patient per primary care worker			-0.888***	-0.827***
			(0.223)	(0.191)
Average Ventilators used				-15.303
				(12.986)
Healthcare spending per capita				0.013*
				(0.007)
Constant	43.694	51.223**	144.398***	41.891
	(31.462)	(25.680)	(42.256)	(61.094)
Observations	3,104	3,104	3,104	3,104
Adjusted R-squared	0.747	0.790	0.798	0.800

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Although quality of care is relevant, model (4) reduces the potential value of including a quality control variable. Note that the overall hospital rating loses its significance and decreases in size. Moreover, the efficiency of care and the patient's experience ratings are displayed negative and significant coefficients, whereas the other quality measures (timing and safety of care, readmission rate and mortality rate) seem less relevant. Disregarding the individual coefficients of the additional control variables, the main supply variables do not swap signs, lose significance or in- or decrease in size. Therefore, I conclude that additional supply-side control variables are mostly correlated with the constant in the model and a fixed-effect model can account for this variance. Since including additional supply and quality of supply control variables come with a trade-off of excluding Counties that do not have any hospital supply, further models will not include additional supply and/or quality controls unless specified otherwise.

However, a supply-side model without control variables would be futile. Table 9 covers the full state-FE supply-side model including medical and socioeconomic mortality covariates. Both types of mortality covariates will be discussed after analysing the full supply-side model. The number of deaths, cases, vaccinated and lockdown policies are time-variant, so time-variance is present in the model. Interestingly, the main supply variables are comparable to the naïve OLS regression, although most coefficients are now significant and smaller in size. This indicates that the constant in the time-invariant models were indeed able to absorb a large part of regional variation. Although a state-level FE mitigates this problem, it also excludes healthcare expenditures from the model. Healthcare expenditures are measured at the state level rather than the county level and this implies that the state-level fixed effects account for this instead of control in the model separately. Unfortunately, no data was available at a lower level, so funds can not directly be assessed in a State-FE model. The positive association of healthcare expenditures is discussed in the next section.

Turning to the time-variant controls for the course of the pandemic. The number of cases (increasing) and the Stringency Index (decreasing) behave as expected. However, the positive sign of vaccinations is unexpected and an explanation for this would be the presence of an omitted variable bias correlated with both the fully vaccinated and the number of deaths. This can be the case for comorbidities: individuals with comorbidities are likelier to be fully vaccinated and regional mortality is positively associated with comorbidities. Not accounting for these medical mortality covariates fully may explain the positive sign. In an uncontrolled model, the fully vaccinated produces a negative significant coefficient, yet it is positive in a controlled one. Considering this unexpected sign of vaccines, a takeaway of the model should be that comorbidities are not fully included in the medical mortality covariates, discussed more in-depth in the next section.

Table 8: Extensive supply side model without medical or socioeconomic mortality covariates

	(1)	(2)	(3)	(4)
	Deaths	**Deaths**	**Deaths**	**Deaths**
Hospital beds	0.260	0.260	0.259	0.258
	(0.422)	(0.422)	(0.422)	(0.421)
Staffed beds	1.366***	1.366***	1.365***	1.366***
	(0.390)	(0.391)	(0.390)	(0.393)
ICU beds	-5.896**	-5.885**	-5.877**	-5.884**
	(2.730)	(2.727)	(2.727)	(2.732)
Hospitals	-43.892	-43.959	-43.736	-43.871
	(44.334)	(44.485)	(44.494)	(44.743)
Average Beds utilized	0.630	0.650	0.621	0.638
	(0.420)	(0.432)	(0.432)	(0.443)
Patient per physician	-1.271***	-1.262***	-1.204***	-1.147***
	(0.326)	(0.323)	(0.324)	(0.319)
Patient per other primary care worker	-0.889***	-0.896***	-0.908***	-0.921***
	(0.231)	(0.234)	(0.234)	(0.240)
Average Ventilators used	-12.524	-12.164	-12.670	-12.303
	(11.713)	(11.615)	(11.581)	(10.871)
Healthcare spending per capita	0.012	0.015*	0.015*	0.016*
	(0.008)	(0.008)	(0.008)	(0.009)
Emergency Services Hospitals %	1.420***	1.444***	1.484***	1.408***
	(0.512)	(0.520)	(0.519)	(0.491)
Non-profit Hospitals (Base: Government hospitals)		-17.381*	-13.673	-12.277
		(9.932)	(10.147)	(9.541)
For-profit Hospitals (Base: Government hospitals)		-0.941	-1.595	-4.250
		(19.266)	(19.299)	(19.488)
Critical care Hospitals (Base: Acute care Hospitals)	39.397	39.434	42.311*	42.933*
	(24.571)	(25.166)	(24.993)	(21.897)
Children's care Hospitals (Base: Acute care Hospitals)	-6.017	-9.281	-6.083	-21.724
	(79.401)	(77.889)	(79.391)	(81.296)
Hospital rating (1-5)			-15.444**	-3.052
			(6.719)	(7.896)
Efficiency of care rating (1-5)				-17.066*
				(9.875)
Mortality rate rating (1-5)				4.976
				(12.812)
Patient's experience rating (1-5)				-9.898**
				(4.286)
Readmission rate rating (1-5)				-5.249
				(4.386)
Safety of care rating (1-5)				-2.848
				(2.846)
Timing of care rating (1-5)				1.336
				(6.253)
Constant	-86.411	-104.048	-57.662	-18.993
	(62.806)	(66.063)	(67.219)	(74.194)
Observations	2,753	2,753	2,753	2,753
Adjusted R-squared	0.801	0.801	0.801	0.801

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Considering that hospital beds are the total denominator for total bed supply, its coefficient should be jointly read with the number of staffed beds and ICU beds. Staffed beds are beds that are created for patient care (ranging from giving birth to long term care). Having patient care reduces the expected number of deaths, similar to ICU beds. Yet, it is not so relevant to zoom in on those coefficients, but more on the supply side mechanism it shows. Hospitals are, given a fixed number of licensed hospital beds, able to reduce the expected number of covid deaths by creating a higher number of staffed beds and/or increasing the number of beds in the intensive care. Hospitals may manage to meet short term demand for hospital services by reallocating beds and care towards infected patients, and the more the hospital does so, the fewer the number of deaths. If the hospital fails to do so (# hospital beds are high, but # ICU beds are low), a higher number of deaths are expected. This is what the coefficients jointly indicate rather than hospital beds are mortality increasing. However, it could be that the number of hospital beds coefficient is upwards biased since comorbidities and supply are positively correlated. Still, one would expect that this would be applicable to staffed beds and ICU, and these coefficients are negative. Additionally, the ratio of these three coefficients is likely to be similar in a bias-free model, implying that reallocation is the main supply-side force of decreasing covid mortality.

Although the supply data does indicate that there is some benefit to reallocating healthcare services, the coefficients are relatively small. The average county has a supply of 323 licensed beds, of which 9.6% consists of ICU beds and 85.3% of staffed beds. Excluding Counties with zero hospital supply, this yields an average of 408 licensed beds. In an unrealistic scenario in which a county was able to increase the share of ICU beds to 100%, an expected 50 regional deaths could be prevented in a year, according to this FE model. This weak effect was somewhat expected, due to some literature finding that there is no significant relationship between the number of ICU beds and covid mortality. On the other hand, 2,437 Counties are in the hospital database: for those regions, 121.850 deaths could be prevented. Shifting 10% of the total hospital supply to the intensive care units would decrease the expected number of deaths by 12.185 at the national level. Nonetheless, the possible benefits of increasing healthcare capacity may be small when adding hospital beds only. Reallocating healthcare towards patient care or intensive care seems more beneficial for driving down covid mortality and this should be the main takeaway.

Doctors and primary care workers are scaled to the population. It depicts how many patients a doctor/primary care worker serves in a county. If this ratio increases, a higher number of deaths are expected for doctors (physicians). More physicians therefore imply less deaths, opposed to other types of primary care provides (nurses, assistants). Both physicians and nurses/assistants are concerned with the direct care of an infected individual, if necessary. A division in the sign is not straightforward to explain. The coefficient is likely to have a downward bias. More healthcare personnel is required to treat comorbidities, but can prevent covid mortality to some extent.

The usage of beds and ventilators have an expected sign. Ventilators/beds are used if a patient has trouble with breathing (a severe symptom of covid). A strong positive association is therefore expected, which the model shows. The use of beds or ventilators implies healthcare resources are relatively more used in that region and therefore serve as a control for healthcare pressure. Lastly, the most significant coefficient is the number of hospitals in a county. Counties with relatively more hospitals are expected to decrease covid mortality with circa 11 deaths per hospital.

Table 9: The supply side model controlling for socioeconomic and medical mortality covariates.

	Coefficient	95% CI
Hospital beds	0.120***	
	(0.001)	(0.119 - 0.122)
Staffed beds	-0.042***	
	(0.001)	(-0.045 - -0.040)
ICU beds	-0.241***	-
	(0.005)	(-0.251 - -0.231)
Hospitals	-11.074***	
	(0.084)	(-11.237 - -10.910)
Average Beds utilized	0.172***	
	(0.006)	(0.159 - 0.184)
Patients per physician	0.212***	
	(0.005)	(0.203 - 0.221)
Patient per other primary care worker	-0.170***	
	(0.002)	(-0.175 - -0.166)
Average Ventilators used	1.202***	
	(0.059)	(1.086 - 1.318)
Cases t-14	0.015***	
	(0.000)	(0.015 - 0.015)
Fully vaccinated per 100 t-14	0.145**	
	(0.061)	(0.026 - 0.264)
Stringency Index t-14	-0.048***	
	(0.010)	(-0.067 - -0.029)
Constant	-857.279***	
	(17.694)	(-891.959 - -822.600)
Observations	919,310	
Number of states	42	
Adjusted R-squared	0.842	
Medical mortality covariates	Yes	
All socioeconomic mortality covariates	Yes	

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Medical mortality and socioeconomic covariates

Medical mortality covariates of covid can be defined broadly. To categorize these variables, the model has a functional approach: all control variables that can explain differences in health status, assuming that health status can account for covid mortality. Unfortunately, the prevalence of all comorbidities is not known at the county level. Noteworthy health controls are diabetes, obesity, age, psychical health, mental health, smoking and drinking behaviour. In this section, attention is devoted to the behaviour of medical mortality covariates and the differences in a FE and OLS model. This yields four different model specifications in Table 10.

Due to a time-invariant explanatory variable (supply), a State-FE model does not differ significantly as opposed to an OLS regression as it solely captures unobservable between-State rather than within-State variation. For all four model specifications, the categorization in the type of hospital beds yields the same result: total beds and staffed beds are associated with an increase in mortality, yet the ICU are death decreasing. As the socioeconomic medical covariates are not included, the signs and magnitude are different from the main supply model.

Most health controls have an expected sign: diabetes, age, physically inactive, physically unhealthy days are all mortality increasing. The contrary applies to obesity, mental well-being, low birth weight, drinking and smoking behaviour. Although some of those controls may be unambiguous (mental well-being, smoking and drinking), obesity should be positively associated with covid mortality, as medical research indicates. An explanation for an unexpected sign of health controls is that the model does not control for socioeconomic outcomes. And as discussed before, this paper argues that both medical and socioeconomic mortality covariates should be used to explain variations in regional mortality. In general, the four supply model specifications do not differ that much when including medical mortality covariates. Only the patient per physician rate changes sign in model (4). A rationalization is that unobservable between state variation is in some way positively correlated to the total supply of doctors and negatively with covid deaths within a county (e.g., educational attainment). Also, note that the vaccine and Stringency Index coefficient both change sign compared to Table 10. The positive association of healthcare expenditures in (1) and (3) is not surprising. Perone et al (2021) deploy a similar supply-side model and find a positive association when controlling for socioeconomic variables. The authors state that healthcare expenditures are only one measure of healthcare effectiveness, so a positive sign may be expected when controlling for multiple effectiveness measures. On the other hand, the models of Bonovas (2012, based on Swine Flu data) and Sorci et al (2020) indicate a negative association.

Some health variables do not have the expected sign when trying to explain the regional number of deaths. For instance, the level of obesity and diabetes (two comorbidities of covid) has a negative sign, whereas the medical literature is unanimous on a positive sign. All things considered; the health control variables do a poor job in explaining covid mortality. Firstly, suppressing health-related variables does not alter the supply model coefficients significantly. The supply-side model is therefore not strongly correlated with those variables. Secondly, obesity is a variable that maintains a negative sign for several model specifications (only supply and health as control variables, only health, only socioeconomic covariates). It should be noted that a weakness of this paper is the health-related side of modelling covid mortality since many relevant health covariates are not included. Even when controlling for many possible cofounders and using fixed effects, there is a possible omitted variable bias in the model for health-related coefficients. Comorbidities which should be included are the regional prevalence of cancer, hypertension, cardiac disease, and chronic respiratory disease. Since this paper cannot dispute articles from the medicine academics based on a FE-regression, I conclude that an omitted variable bias is present in the model. Most health variables differ in the correlation of supply-side variables, this may yield a positive or negative omitted variable bias based on the effect of the cofounder on the number of deaths. For instance, the coefficient of age is downward biases since elderly have relatively more comorbidities.

There is a vast array of academic literature on possible socioeconomic influences on covid mortality (Table 4). To provide an overview, the following categorization of socioeconomic control variables is used: demographics (excluding age), socioeconomic status (including education) and community differences (commuting, political preferences, meteorology, and housing). For all categories, two models are specified: (1) the supply-side model including only socioeconomic variables of that category and (2) the full supply model including all socioeconomic variables for comparison. The goal is to illustrate the gravity of the type of socioeconomic mortality covariates and the difficulty to decipher the "true" empirical model of covid regional mortality.

Starting with demographics in Table A7, the explanatory power of model (1) is surprisingly higher than the full supply-side model. Even so, most demographic control variables do not have the expected effect on covid mortality. Most of these control variables do change sign when controlling for all three categories of socioeconomic mortality covariates. The differences in these models display why an empirical analysis of regional covid mortality is highly subject to an omitted variable bias. Virtually all papers include demographic control variables to account for population differences, notwithstanding it is equally an area that is correlated with other types of mortality covariates. For instance, the fraction of youth is associated with mortality increasing (+5), whereas this is mortality decreasing (-1.5) in the full supply-side model. The same principle applies to the total population, which is mostly mortality increasing in model specification (1). When controlling for these three categories of control variables, most control variables have the expected sign based on literature. Contrary to Michelozzi et al (2020), the share of females is estimated to be positively related to covid mortality. This is due to the incompleteness of comorbidities in the model: comorbidities that are positively correlated with the female gender and covid mortality create an upward bias. For instance, hypertension is more prevalent for females (Tran et al, 2018) and positively associated with covid mortality. And teenagers are expected to have less comorbidities than elderly, explaining why the fraction of youth is positively associated at first.

Regarding ethnicity, the expected death per cent point is higher for the share of the Black and American Indian population than White and Hispanic. Some papers have assessed the racial mortality disparities of Black and White communities, and this model hints at the same outcome (three expected deaths per percentage point increase of Blacks relative to White). Also, note the significant and considerable negative coefficient of Native Hawaiian. This may be due to a data technicality. Hawaii is one of the harder hits regions but lacks data on numerous control variables and is therefore not included in the regression model. On average, 0.1% of the County population consists of Native Hawaiians. The standard deviation for this ethnicity is, therefore, larger and may be associated with downward trends in regional covid mortality. Furthermore, some basic outcomes of Sannigrahi et al (2020) are confirmed in the model: a higher population, a higher population density (overcrowding) and less rural communities see a higher number of casualties. Except for gender, all covariates are comparable to those found in Table 4.

The second categorization of socioeconomic mortality covariates is socioeconomic status. These variables include information on median household income, unemployment, poverty, access to health, uninsured and educational attainment (Table A8). Opposed to the demographic control variables, many of the coefficients have the same sign in both model (1) and (2), except for access to health and the fraction of uninsured for healthcare services.

The rationale for including a set of income controls (income, poverty, and inequality) stem from the models of Stojkoski et al (2020) and Brown & Ravallion (2020). In these models, inequality was associated with mortality increasing, and the same holds for the 80th-20th income ratio and individuals earning below the poverty line. Brown & Ravallion (2020) argued that the expected sign of median household income varies when including poverty, as particular income groups may respond differently to social distancing policies. In this model, both poverty and median household income are positively associated, and the same result was found in the author's model.

Two associations should be highlighted found in Table A8. The first is the unexpected negative sign of the unemployment rate: several papers have established a positive association. Again, these types of empirical models are at risk of biases, so it is a possibility that other papers were not able to control for sufficient outcomes. Secondly, the fraction of uninsured individuals is significantly mortality increasing (five times the size of ICU supply and 1.5 times building a new hospital). This indicates that the widely debated issue with American privatized healthcare and access to healthcare services is also a concern in the event of a pandemic.

The modal educational attainment is additionally considerable in size. Comparing to primary level schooled (primary schooled or no diploma), both secondary education level (high school) and tertiary educational attainment (college or university degree) decrease expected regional mortality significantly. The difference in secondary and tertiary educational attainment is not sizeable. Overall, the SES control variables appear to have a common trend: if the SES indicators are poor in a county, then the expected number of deaths may increase ceteris paribus. This is also why many papers focused on racial disparities in covid mortality, which can be partially explained by differences in the SES indicators. I conclude that the SES indicators are highly relevant indicators for variations in regional covid mortality at the county level.

The final category consists of a set of community outcomes (political, commuting and housing) that the literature marks as relevant in Table A9. The main supply-side variables in model (1) do not differ significantly from the full supply-side model, which is a sign that community variables are a relevant input. Starting with traffic movements, owning a vehicle is a significant predictor of decreasing covid mortality. The use of public transit was reported to have a positive association (Knittel & Ozaltun (2020); McLaren (2020). If the individuals who do not own a car, are relatively more likely to use public transit, then this outcome is similar to the public transit models. It is however a different control variable, so the direct comparison might be inadept. The commuting variables do reveal a pattern: communities, where relatively more traffic movements happen (average traffic volume, long commutes), see an increase in the number of deaths, controlled for the fraction of individuals that drive alone to work (so no carpooling). Traffic movements have been the centre of debate in many countries, with restrictions on the distance citizens can travel from home (e.g. 15 km). Accordingly, these types of restrictions are based on a rationale.

Political preferences do play a role in covid mortality. As Alcott (2020) found, Republican Counties are hit later and harder in the pandemic than Democratic. This is why the 2016 Republican-Democrat election difference is a negative coefficient (those counties are Republican at the start of the pandemic). As the pandemic continues, Republican counties are worse off, indicated by the positive sign of the 2020 difference. The model discovers this mechanism displayed by Alcott (2020) and political preference is, therefore, a relevant and considerable control factor.

Turning to the housing outcomes, the fraction of homeowners is negatively associated with regional mortality, as was also reported by Desmet & Waziarg (2021). Areas that are faced with severe housing costs and housing problems, and possibly more homelessness, are also worse hit in terms of expected deaths. Some other outcomes of Perone et al (2021) & Zhu et al (2020) are also found by the full supply-side model. Pollution (PM2.5) is death increasing and temperature associated with death decreasing, although the coefficients indicate that these controls have a smaller impact than other control variables.

Table 10: Supply model with lagged pandemic data and medical mortality covariates

	(1) OLS	(2) FE	(3) OLS	(4) FE
Hospital beds	0.598***	0.611***	0.601***	0.614***
	(0.020)	(0.002)	(0.020)	(0.002)
Staffed beds	0.181***	0.170***	0.172***	0.166***
	(0.014)	(0.003)	(0.014)	(0.003)
ICU beds	-3.469***	-3.344***	-3.437***	-3.304***
	(0.127)	(0.012)	(0.126)	(0.012)
Hospitals	-66.732***	-70.998***	-66.379***	-70.239***
	(2.066)	(0.196)	(2.083)	(0.200)
Average Beds utilized	0.775***	0.774***	0.798***	0.865***
	(0.023)	(0.016)	(0.025)	(0.017)
Patient per physician	-0.150***	-0.138***	-0.034***	0.079***
	(0.010)	(0.010)	(0.009)	(0.012)
Patient per other primary care worker	-0.272***	-0.279***	-0.303***	-0.378***
	(0.006)	(0.005)	(0.006)	(0.006)
Average Ventilators used	-12.944***	-12.553***	-12.403***	-10.322***
	(0.614)	(0.154)	(0.587)	(0.160)
Healthcare expenditures per capita	0.022***		0.033***	
	(0.000)		(0.000)	
Cases t-14	0.019***	0.019***	0.019***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
Fully vaccinated per 100 t-14	-2.513***	-2.754***	-2.632***	-2.759***
	(0.267)	(0.162)	(0.274)	(0.165)
Stringency Index t-14	0.528***	0.419***	0.429***	0.416***
	(0.022)	(0.027)	(0.026)	(0.027)
Access to exercise %			-0.003	-0.068***
			(0.010)	(0.016)
Average mentally unhealthy days			-16.846***	-107.350***
			(1.604)	(2.290)
Average physically unhealthy days			20.542***	190.946***
			(2.127)	(2.786)
Diabetes %			0.751***	0.799***
			(0.035)	(0.094)
Median Age			0.433***	1.386***
			(0.045)	(0.083)
Obese %			-1.135***	-0.918***
			(0.044)	(0.073)
Excessive drinking %			-1.509***	-2.406***
			(0.111)	(0.264)
Fair or poor health %			3.987***	-6.026***
			(0.151)	(0.251)
Low birthweight %			-5.030***	-9.664***
			(0.313)	(0.216)
Physically inactive %			2.872***	3.517***
			(0.056)	(0.077)
Smokers %			-6.408***	-6.736***
			(0.139)	(0.264)
Constant	-137.396***	46.871***	-191.341***	-61.117***
	(2.433)	(1.427)	(4.826)	(10.491)
Observations	1,051,047	1,051,047	1,025,759	1,025,759
R-squared	0.734	0.729	0.735	0.733
Number of states		49		49

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Robustness analysis

The last section consists of two robustness analyses of the supply side of the covid mortality model. All socioeconomic and medical covariates are included for each model. The first robustness check is whether the model specification alters the conclusions of the association between supply-side factors and regional covid mortality. Table A10 compares the state-level FE model with three different models: the same FE model with quality and supply control variables, a standardized OLS coefficient and an OLS regression with no time-variance. As was analysed earlier, the additional quality and supply control variables do not alter the coefficients significantly, justifying the exclusion of these controls in the main analysis (model 2) with the benefit of including counties in which supply is zero. All quality control variables are negatively associated with the number of deaths and significant. Additionally, for-profit hospitals have an associated 8,2 higher death number than government hospitals. However, the model loses a small fraction of explanatory power in terms of the R-squared. The type, ownership and quality of supply therefore seem less relevant when analysing regional variation.

Data is sensitive to how it is measured, and this may give measurement or outlier bias in the current model. Standardizing all variables to the unit of 1 overcomes the problem of measurement bias (although most control variables are measured in percentage points in the FE model). On the other hand, standardized coefficients assume that the relative importance of variables within a model can be expressed by a constant scale of standard deviation, and the model may be unfit to do so in this case. The standardized coefficient displays a similar sign to the FE model, except for the fully vaccinated per hundred. Both the Stringency Index (lockdown policies) and vaccinated are negatively associated with deaths, which did not occur in any of the FE models. The two most important variables are the number of mortalities increasing hospital beds and the number of cases according to the model. Other supply-side variables tend to be small (the ICU coefficient is significantly smaller for example). Concluding, this model specification does not support the conclusion that counties, that can reallocate resources towards intensive care, are more successful in decreasing covid mortality. It does support that outlier or measurement bias is not the driver of the found results. The time-invariant model (4) does support this outcome; however, the R-squared of 0.97 is too problematic. As described throughout this paper, the regional constant can account for a large share of the variance and it does in this type of analysis. Ultimately, this harms the validity of the meta-regression considerably. The current state-FE methodology produces results that are similar to other model specifications and balances methodological issues in a more concise matter than the three other specified models.

A robustness analysis also covers the specification or measurement of relevant variables. Four different specifications are compared in Table A11: not using lags for time-variant data (1), using the CFR as the dependent variable (2), using the daily change in time-variant data (3), and using the share of ICU beds instead of the division of beds (4).

The non-lagged Stringency Index loses its significance in the model (1) of Table A11. Additionally, the R-squared decreases slightly and the effect of total cases increases relative to the FE supply-side model. The supply variables of interest remain similar and not much change is observed. The argument to use lagged variable proves to be sensible. The main takeaways of the FE supply model are stable since these occur in most estimations, yet it is a poor model to explain regional differences in the CFR (2) or daily deaths (3). The coefficients are close to zero in both models and have little variation. Both dependent variables are small in size, as the CFR is a percentage with little variation. The number of daily deaths is also small with a low variation. An additional weakness of the supply model is that it can only be used to estimate the number of regional deaths, which can be a threat to external validity. On the other hand, model (4) directly specifies the share of ICU beds as the dependent variable and finds a small negative association as expected, similar to Karaca-Mandi et al (2020). This reinforces the main takeaway of the supply-side model: counties that can raise ICU supply relative to total supply, are associated as mortality decreasing. Given that this is a confirmation of the main state-FE model used in this paper. I conclude that the model is not driven by measurement bias, model or variable specification and therefore the results are robust.

VI - Discussion

This paper was concerned with a meta-analysis on the relationship of regional covid mortality and supply of healthcare services. Several points should be raised after an extensive literature review and empirical analysis. Firstly, numerous papers have been concerned with this exact relationship since it is of great significance during the pandemic. However, most papers do not adequately or systematically define supply when examining this relationship. Perone et al (2021) include numerous dimensions of supply within their model based on hospital beds, healthcare expenditures and medical personnel. Yet, most of the academic research assesses the supply of hospital beds and medical personnel, excluding possible resource availability, healthcare pressure or funding of healthcare services. Those components are certainly relevant when shedding light on the supply-side of healthcare in a pandemic and its linked outcome of covid mortality.

Secondly, another dimension of supply that most papers fail to capture is the division of healthcare supply based on the demand of covid infected patients for healthcare services. This occurs if models do not separate between normal and intensive care hospital beds, but also if ventilators are not accounted for. Sen-Crowe et al (2020) separate global hospital bed supply, acute care beds and intensive care units. Although this paper does not directly focus on this distinction within hospital bed supply, it is an example of illustrating that numerous factors are likely to affect covid mortality. Furthermore, Moreira (2020) analyses the supply of ventilators to assess regional covid mortality variations in Brazilian provinces. Both papers show that the starting point of analysis, including the supply-side of healthcare services, is to assess how the relevant supply dimension should be categorized or defined.

Thirdly, it proved to be valuable to include both medical and socioeconomic mortality covariates. Although medical mortality covariates are not properly controlled for in this paper, excluding socioeconomic mortality covariates reduces the explanatory power of the supply-side model and the combination of the two is therefore highly relevant. To discover the true empirical model of regional covid mortality thus requires an interdisciplinary focus, combining both medical and socio-economic knowledge. Since county-level data on the prevalence of comorbidities is scarce, such analysis may require different methods or data collection.

Fourthly, the academic debate on the significance of intensive care supply (Malki et al (2020); Moreira (2020); Bravata et al (2021); Knittel & Ozaltun (2020); Stojkoski et al (2020)) for covid mortality is due to not accounting for the different dimensions of healthcare services. This debate does not occur in papers that assess the total number of hospital beds as the explanatory variable. The main takeaway of the supply-side model answers this contradiction to some extent. Regional mortality is expected to decrease if a county is successful in reallocating its healthcare capacity to meet short term covid demand. As healthcare capacity is inflexible, this reallocation mechanism of supply does have a theoretical basis. On the other hand, it must be noted that the hospital bed coefficients are relatively small in the model: one extra intensive care bed at the expense of a regular hospital bed does not decrease covid mortality significantly. Therefore, this supply-side mechanism both explains why there is an academic debate on the significance and the expected sign of intensive care units.

Healthcare policymakers should therefore critically assess the definition of healthcare capacity when preparing or managing a surge in short-term healthcare demand. Treatment of infected covid patients requires multiple dimensions of healthcare services: the type of hospital beds, ventilators, masks, medical personnel, and funds are the most apparent dimensions. Ultimately, healthcare supply is inflexible in the short term, so expanding healthcare capacity is unlikely to be a direct solution since healthcare capacity is reallocated to meet short-term demand. And this pragmatic solution of reallocating is associated to be mortality decreasing, implying that prioritizing care is effective in the event of a pandemic. Nevertheless, it also threatens a reduction of long-term healthcare capacity as regular care is faced with backstops and postponements. A policymaker should therefore identify which link of the healthcare supply chain is under the most pressure and reallocate capacity towards this input factor. A long-term solution could therefore be to accommodate swift reallocation (e.g., by emergency facilities or training of personnel) of healthcare input factors to handle surges in short-term demand.

The methodology and findings of this paper contain several limitations. Firstly, the supply-side variables are time-invariant. This weakens the internal validity of the empirical model and could be improved if this type of variation were accounted for. Future research may be able to exploit both time variation in hospital bed supply and covid mortality. Secondly, the prevalence of the relevant comorbidities within counties is not adequately captured due to data unavailability, and this yields an omitted variable bias affecting elements of the model. Possible improvements would be to include the prevalence rate of hypertension, chronic diseases, cardiac disease, and cancer. Thirdly, the model is not able to explain regional variations of deaths when adjusting the dependent variable to the case-fatality ratio or daily deaths. This is a threat to the external validity, as the reported coefficients may only be applicable in the American-county setting analysing total deaths. Fourthly, including the number of ventilators available at the hospital level would improve the model, as the average use is included in the model as a control variable. This control variable is only partially able to exploit the time-variation of the supply of ventilators. Finally, this research does not shed light on the costs and benefits of reallocating healthcare capacity. An evaluation of the optimal healthcare capacity during a pandemic requires to adequately assess the direct prevention of deaths and the indirect health outcomes due to a backlog of normal care as the benefits to it. The benefit of reallocation of healthcare can be derived from the empirical model, yet it lacks a cost estimation to assess to which extent it is beneficial to reallocate healthcare capacity to the treatment of infected patients (e.g., limitations to transferring medical personnel).

To conclude, several supply-side factors and their association with covid mortality are analysed by exploiting regional variation at the county level. Additionally, medical and socioeconomic mortality covariates have been included in a Fixed-Effect model. As the American healthcare and pandemic setting is unique, further analysis would be needed to decipher how several socioeconomic mortality covariates have affected the course of the pandemic. The pandora's box of these type of relationships has just been opened by academics: one may expect to read future literature on how the socioeconomic status and private health insurance of an American is not only highly relevant for the citizen's quality of life, but also in the event of a global pandemic.

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Appendix

Table A1: State-by-state cases, deaths, vaccinations, and CFR.

	Cases	**Deaths**	**CFR** %	**Vaccinations** per hundred
Alabama	511087	10436	2	19.6
Arizona	835765	16733	2	24.2
Arkansas	325349	5533	1.7	21.7
California	3640704	57469	1.6	24.2
Colorado	452174	6148	1.4	23.9
Connecticut	295648	7823	2.6	29.0
Delaware	91741	1526	1.7	24.5
Florida	2000840	32712	1.6	23.1
Georgia	1015421	17954	1.8	18.1
Hawaii	28762	450	1.6	26.7
Idaho	177501	1944	1.1	21.4
Illinois	1223884	23070	1.9	24.8
Indiana	680420	12926	1.9	21.4
Iowa	344644	5675	1.6	25.8
Kansas	302223	3917	1.3	24.5
Kentucky	423989	5777	1.4	26.1
Louisiana	437872	9953	2.3	22.3
Maine	48292	728	1.5	27.8
Maryland	399200	8114	2	24.5
Massachusetts	576651	16822	2.9	28.0
Michigan	690929	16885	2.4	23.4
Minnesota	503789	6777	1.3	26.1
Mississippi	302677	6955	2.3	21.4
Missouri	530160	8167	1.5	21.8
Montana	103042	1415	1.4	25.8
Nebraska	206685	2243	1.1	24.9
Nevada	300972	5171	1.7	23.0
New Hampshire	79242	1212	1.5	27.1
New Jersey	861394	24134	2.8	27.4
New Mexico	165808	3481	2.1	32.3
New York	1779291	48916	2.7	24.9
North Carolina	900319	11848	1.3	24.2
North Dakota	101602	1461	1.4	28.3
Ohio	998819	18339	1.8	23.3
Oklahoma	432781	4788	1.1	26.5
Oregon	161342	2373	1.5	23.2
Pennsylvania	989336	24841	2.5	24.4
Rhode Island	120584	2560	2.1	28.3
South Carolina	540390	8977	1.7	22.0
South Dakota	113643	1873	1.6	29.6
Tennessee	775509	11487	1.5	20.4
Texas	2752597	47462	1.7	21.4
Utah	379249	2047	.5	20.3
Vermont	17547	219	1.2	27.6
Virginia	603748	10106	1.7	24.9
Washington	357376	5224	1.5	24.4
West Virginia	137478	2600	1.9	26.1
Wisconsin	629167	7241	1.2	25.6
Wyoming	55581	693	1.2	23.2
Total / Average	**29.403.224**	**535.205**	**2,0**	**23,7**

Table A2: Descriptive statistics on healthcare supply and quality

	Mean	Std. Dev.	min	max	N
Hospital beds	303.3	1057.9	0	23854	3104
Staffed beds	258.4	926.5	0	22423	3104
ICU beds	29.1	104.4	0	2262	3104
Hospitals	2.1	4.7	0	106	3104
Average Beds utilized	29	22.3	0	100	3104
Patient per physician	51.6	35.6	0	514.4	3104
Patient per other primary care worker	83.8	61.9	0	1557	3104
Average Ventilators used	1.9	2.4	0	33	3104
Healthcare spending per capita	7939.1	856.8	5982	10559	2753
Emergency Services Hospitals %	91.8	17.3	0	100	2753
Hospital rating (1-5)	3.3	.8	1	5	2753
Efficiency of care rating (1-5)	2.8	.7	1	5	2753
Mortality rate rating (1-5)	2.9	.6	1	5	2753
Patient's experience rating (1-5	3.3	1.3	1	5	2753
Readmission rate rating (1-5)	3.3	1.3	1	5	2753
Safety of care rating (1-5)	3.4	1.3	1	5	2753
Timing of care rating (1-5)	3.6	1.2	1	5	2753

Table A3: Descriptive statistics of demographic and community variables

	Mean	Std. Dev.	min	max	N
<18 year-old %	22.1	3.4	7.1	42	3104
American Indian %	2	6.5	0	85.7	3104
Asian %	1.5	2.7	0	43	3104
Black %	9	14.3	0	85.4	3104
Female %	49.9	2.2	26.8	56.9	3104
Hispanic %	9.7	13.8	.6	96.4	3104
Mean C	17.4	3.9	0	30.8	3104
Native Hawaiian %	.1	.4	0	13	3104
PM2.5 (Pollution)	52.7	36.4	3	99	2812
Population density	224	1019.6	.1	37510.5	3104
Rural community %	58.6	31.4	0	100	3104
Total Population	26668.9	94402.4	22	2997389	3104
White %	76.4	19.8	2.7	97.9	3104

Table A4: Descriptive statistics of health variables

	Mean	Std. Dev.	min	max	N
Access to exercise %	62.5	23.2	0	100	3104
Average mentally unhealthy days	4.2	.6	2.5	6.3	3104
Average physically unhealthy day	4	.7	2.4	6.6	3104
Diabetes %	12.1	4.1	1.8	34.1	3104
Excessive drinking %	17.5	3.1	7.8	28.6	3104
Fair or poor health %	17.9	4.7	8.1	41	3104
Low Birthweight %	8.2	2	2.9	24.4	3007
Median age	41.3	5.4	21.7	67	3104
Obesity %	32.9	5.4	12.4	57.7	3104
Physically inactive %	27.4	5.7	9.5	49.9	3104
Smokers %	17.4	3.5	5.9	41.5	3104

Table A5: Descriptive statistics of SES and political preference

	Mean	Std. Dev.	min	max	N
80-20 percentile Income ratio	4.1	1.4	0	8.8	3102
Limited Access to Healthcare %	8.6	8.2	0	71.8	3085
Median HH income	52670.4	13811.4	25385	140382	3104
Below poverty line %	16.4	6.5	1.8	48.7	3104
Unemployment %	4	1.4	.7	18.3	3104
Uninsured %	11.4	5.1	2.3	33.7	3104
Some college degree %	30.8	5.2	5.2	60.6	3104
Bachelor's degree %	21.9	9.5	0	77.6	3104
Lower than HS diploma %	13.1	6.3	1.1	73.6	3104
HS diploma %	34.2	7.2	7.3	57.4	3104
Republican County 2016 %	84.5	36.2	0	100	3104
Republican County 2020 %	82.9	37.7	0	100	3104

Table A6: Correlations of supply and COVID-19 deaths

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Total deaths	1.000								
(2) Hospitals	0.560	1.000							
(3) Hospital beds	0.659	0.947	1.000						
(4) Staffed beds	0.655	0.951	0.994	1.000					
(5) ICU beds	0.595	0.942	0.975	0.976	1.000				
(6) Patient per physician	0.072	0.221	0.231	0.227	0.224	1.000			
(7) Average Ventilators used	0.174	0.215	0.307	0.303	0.296	0.330	1.000		
(8) Average Beds utilized	0.116	0.189	0.216	0.213	0.201	0.264	0.451	1.000	
(9) Healthcare expenditures per capita	0.070	0.014	0.037	0.037	0.018	0.170	0.036	0.055	1.000

Table A7: Supply model including socioeconomic mortality covariates - Demographics.

	(1) FE	(2) FE
Hospital beds	0.224***	0.125***
	(0.002)	(0.001)
Staffed beds	0.455***	-0.045***
	(0.002)	(0.001)
ICU beds	-2.622***	-0.223***
	(0.009)	(0.005)
Hospitals	-22.131***	-11.922***
	(0.161)	(0.091)
Average Beds utilized	0.477***	0.111***
	(0.013)	(0.007)
Patient per physician	-0.267***	0.249***
	(0.009)	(0.005)
Patient per other primary care worker	-0.570***	-0.196***
	(0.004)	(0.002)
Average Ventilators used	-4.215***	0.813***
	(0.122)	(0.065)
Cases t-14	0.019***	0.015***
	(0.000)	(0.000)
Fully vaccinated per 100 t-14	-3.141***	0.138**
	(0.124)	(0.068)
Stringency Index t-14	0.403***	-0.045***
	(0.020)	(0.011)
American Indian %	7.593***	9.290***
	(0.309)	(0.179)
Asian %	-5.018***	7.418***
	(0.350)	(0.210)
Black %	3.242***	8.113***
	(0.310)	(0.178)
Female %	-4.300***	2.061***
	(0.130)	(0.082)
Hispanic %	2.395***	7.135***
	(0.299)	(0.172)
<18 year %	5.591***	-1.468***
	(0.113)	(0.077)
Native Hawaiian %	8.513***	-18.128***
	(1.310)	(0.789)
White %	7.506***	7.529***
	(0.307)	(0.177)
Rural community %	0.089***	-0.292***
	(0.013)	(0.008)
Total Population	-0.002***	0.001***
	(0.000)	(0.000)
Population density	0.167***	0.033***
	(0.000)	(0.000)
Constant	343.547***	-737.749***
	(33.049)	(19.125)
Observations	1,025,759	827,329
Number of states	49	42
Adjusted R-squared	0.850	0.838
Medical mortality covariates	Yes	Yes
All socioeconomic mortality covariates	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A8: Supply model including socioeconomic mortality covariates - Socioeconomic Status & Education

	(1) FE	(2) FE
Hospital beds	0.615***	0.124***
	(0.002)	(0.001)
Staffed beds	0.166***	-0.045***
	(0.003)	(0.001)
ICU beds	-3.313***	-0.234***
	(0.012)	(0.005)
Hospitals	-70.331***	-11.441***
	(0.201)	(0.084)
Average Beds utilized	0.891***	0.148***
	(0.017)	(0.006)
Patient per physician	0.039***	0.229***
	(0.012)	(0.005)
Patient per other primary care worker	-0.355***	-0.183***
	(0.006)	(0.002)
Average Ventilators used	-10.228***	1.019***
	(0.161)	(0.060)
Cases t-14	0.019***	0.015***
	(0.000)	(0.000)
Fully vaccinated per 100 t-14	-2.757***	0.156**
	(0.166)	(0.061)
Stringency Index t-14	0.413***	-0.049***
	(0.027)	(0.010)
80-20 percentile Income ratio	1.725***	0.779***
	(0.207)	(0.077)
Limited Access to Health %	-1.089***	-0.044***
	(0.045)	(0.017)
Median HH Income	0.000***	0.001***
	(0.000)	(0.000)
Below poverty line %	0.717***	0.124**
	(0.118)	(0.049)
Unemployment rate %	-0.207	-1.415***
	(0.329)	(0.137)
Uninsured %	-0.254*	1.377***
	(0.139)	(0.063)
Majority is secondary level schooled (Base: primary schooled)	-31.456***	-27.260***
	(3.070)	(1.184)
Majority is tertiary level schooled (Base: primary schooled)	-39.066***	-27.067***
	(3.096)	(1.213)
Constant	-78.115***	-712.631***
	(12.976)	(17.333)
Observations	1,019,050	919,310
Number of states	49	42
Adjusted R-squared	0.733	0.837
Medical mortality covariates	Yes	Yes
All socioeconomic mortality covariates	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A9: Supply model including socioeconomic mortality covariates - Community.

	(1) FE	(2) FE
Hospital beds	0.134***	0.120***
	(0.001)	(0.001)
Staffed beds	-0.019***	-0.042***
	(0.001)	(0.001)
ICU beds	-0.125***	-0.241***
	(0.005)	(0.005)
Hospitals	-10.879***	-11.074***
	(0.084)	(0.084)
Average Beds utilized	0.233***	0.172***
	(0.006)	(0.006)
Patient per physician	0.233***	0.212***
	(0.005)	(0.005)
Patient per other primary care worker	-0.229***	-0.170***
	(0.002)	(0.002)
Average Ventilators used	1.571***	1.202***
	(0.060)	(0.059)
Cases t-14	0.016***	0.015***
	(0.000)	(0.000)
Fully vaccinated per 100 t-14	-0.157**	0.145**
	(0.062)	(0.061)
Stringency Index t-14	-0.040***	-0.048***
	(0.010)	(0.010)
Drive alone to work %	-1.092***	0.106***
	(0.025)	(0.028)
Long commute drives alone %	0.534***	0.037***
	(0.012)	(0.013)
No own vehicle %	3.436***	1.863***
	(0.057)	(0.062)
Average traffic volume	0.101***	0.069***
	(0.001)	(0.001)
Difference R-D (2016)	-1.335***	-2.258***
	(0.030)	(0.032)
Difference R-D (2020)	1.678***	2.910***
	(0.029)	(0.033)
PM2.5 (Pollution)	0.010***	0.055***
	(0.003)	(0.003)
Mean °C	-0.469***	-0.656***
	(0.073)	(0.073)
Homeowners %	0.040	-0.631***
	(0.029)	(0.030)
Multi-unit housing %	-4.027***	-6.164***
	(0.041)	(0.044)
Severe housing costs %	0.427***	2.847***
	(0.089)	(0.102)
Housing problem %	2.172***	0.704***
	(0.084)	(0.091)
Constant	237.265***	-857.279***
	(5.037)	(17.694)
Observations	925,672	919,310
Number of states	42	42
Adjusted R-squared	0.831	0.842
Medical mortality covariates	Yes	Yes
All socioeconomic mortality covariates	No	Yes

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A10: Different type of model specifications: fixed-effect, quality & supply controls and standardized coefficient.

	(1) FE	(2) FE	(3) Beta	(4) No time
Hospital beds	0.120***	0.122***	0.400	-0.674
	(0.001)	(0.001)		(0.473)
Staffed beds	-0.042***	-0.043***	-0.060	1.403**
	(0.001)	(0.001)		(0.645)
ICU beds	-0.241***	-0.229***	-0.153	-10.191***
	(0.005)	(0.005)		(2.952)
Hospitals	-11.074***	-11.469***	-0.152	63.154*
	(0.084)	(0.089)		(35.511)
Average Beds utilized	0.172***	0.144***	0.019	-0.530
	(0.006)	(0.007)		(2.651)
Patient per physician	0.212***	0.238***	0.025	-8.569***
	(0.005)	(0.005)		(1.896)
Patient per other primary care worker	-0.170***	-0.184***	-0.051	2.343***
	(0.002)	(0.002)		(0.873)
Average Ventilators used	1.202***	0.943***	0.017	-20.757
	(0.059)	(0.064)		(28.152)
Healthcare spending per capita			0.102	2.512***
				(0.134)
Total cases				0.019***
				(0.000)
Fully vaccinated per 100				-358.707***
				(29.935)
Stringency Index				20.343**
				(8.908)
Cases t-14	0.015***	0.015***	0.683	
	(0.000)	(0.000)		
Fully vaccinated t-14	0.145**	0.134**	-0.002	
	(0.061)	(0.067)		
Stringency Index t-14	-0.048***	-0.045***	-0.015	
	(0.010)	(0.011)		
Constant	-857.281***	-895.787***	.	2,745.930
	(17.694)	(19.586)		(6,054.723)
Observations	919,309	827,329	919,309	2,700
R-squared	0.842	0.843	0.844	0.971
Number of states	42	42	42	42
Medical mortality covariates	Yes	Yes	Yes	Yes
All socioeconomic mortality covariates	Yes	Yes	Yes	Yes
Quality and Supply control variables	No	Yes	No	No

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A11: Different type of variable specifications

	(1)	(2)	(3)	(4)
	No lags	**CFR**	**Daily change**	**% ICU**
Hospital beds	0.118***	0.000***	0.000***	
	(0.001)	(0.000)	(0.000)	
Staffed beds	-0.045***	-0.000***	-0.000	
	(0.001)	(0.000)	(0.000)	
ICU beds	-0.216***	-0.001***	-0.000***	
	(0.005)	(0.000)	(0.000)	
ICU % Total Beds				-0.056***
				(0.019)
Hospitals	-11.058***	-0.036***	-0.001**	-5.004***
	(0.083)	(0.003)	(0.001)	(0.078)
Average Beds utilized	0.170***	0.002***	-0.000	0.096***
	(0.006)	(0.000)	(0.000)	(0.008)
Patient per physician	0.208***	0.002***	0.000	0.298***
	(0.005)	(0.000)	(0.000)	(0.006)
Patient per other primary care worker	-0.163***	-0.001***	-0.000*	-0.155***
	(0.002)	(0.000)	(0.000)	(0.003)
Average Ventilators used	1.040***	0.001	0.002***	2.374***
	(0.059)	(0.002)	(0.000)	(0.068)
Cases t-14				0.015***
				(0.000)
Fully vaccinated per 100 t-14				0.074
				(0.076)
Stringency Index t-14				-0.050***
				(0.012)
Constant	-821.854***	-5.197***	-0.180	-968.758***
	(17.508)	(0.659)	(0.119)	(21.983)
Observations	957,109	957,109	916,609	739,392
Number of states	42	42	42	42
Adjusted R-squared	0.833	0.020	0.001	0.838
Medical mortality covariates	Yes	Yes	Yes	Yes
All socioeconomic mortality covariates	Yes	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1