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Impacts of COVID-19 on Essential Worker Populations in Los Angeles County, California, with a Focus on Healthcare Workers and First Responders

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Impacts of COVID-19 on Essential Worker Populations in Los Angeles County, California, with a Focus on Healthcare Workers and First Responders

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Epidemiology

by

Cynthia M. Beard

2023

ABSTRACT OF THE DISSERTATION

Impacts of COVID-19 on Essential Worker Populations
in Los Angeles County, California,
with a Focus on Healthcare Workers and First Responders

by

Cynthia M. Beard
Doctor of Philosophy in Epidemiology
University of California, Los Angeles, 2023
Professor Anne W. Rimoin, Chair

As the COVID-19 pandemic continues into a third year, estimates of the proportion of Americans that have been infected at least once range from 42-60%, and an estimated 6% of U.S. adults are currently experiencing the effects of long COVID. The pandemic has uniquely stressed workers in many sectors considered essential, from healthcare workers and first responders to farm workers, retail workers, and manufacturers.

This dissertation aims to understand whether and how the impacts of COVID-19 are associated with occupation in the context of Los Angeles (LA) County, California. After an introduction to COVID-19 and its impacts on population mental health and on essential workers, Chapter 2 presents an ecologic analysis using data from the U.S. Census American Community Survey and the LA County Department of Public Health. This analysis examines if LA County communities with a higher share of their workforces in specific occupations (healthcare, first response, education, or food service) were more or less impacted throughout the COVID-19 pandemic. A higher proportion of a community's workforce employed in healthcare or education

was associated with lower COVID-19 impact, while a higher proportion of a community's workforce in first response or food service was associated with higher COVID-19 impact.

Chapters 3 and 4 use data from a longitudinal cohort study of COVID-19 infection risk in LA-based healthcare workers and first responders to conduct longitudinal analyses on risk factors associated with infection risk and mental health outcomes between May 2020-Sept 2021. Nurses had higher odds of anxiety and of trauma response compared to physicians. Moderate and high levels of hospital bed occupancy were associated with higher odds of low resilience compared to a low level of bed occupancy, but were not associated with anxiety level or trauma response.

Infection risk, vaccination rate, and mental health outcomes differed between healthcare workers and first responders. Time since study baseline was associated with most mental health outcomes across models, but the relationship is nuanced.

Finally, Chapter 5 discusses the public health implications of the research, including potential polices and interventions that may better protect the physical and mental health of workers across the economy.

The dissertation of Cynthia M. Beard is approved.

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2023

DEDICATION

First, I wish to dedicate this work to my family and friends, who have supported me throughout the entire process of completing this dissertation, which mostly occurred during a pandemic. My parents have been a source of unwavering love and support, and their belief in me and trust in my decisions empowered me to complete this degree in the way that I needed to complete it. My brother and sister-in-law, Tommy and Jenny, have been a wonderful venting outlet and source of comedic relief when I most needed it. As a former nurse, Jenny was also an important reminder of the necessity of the research I was doing. My partner, Henry, has been unflinchingly supportive of me, especially in the most stressful moments. He has been a wonderful confidant and has helped me think through many important decisions and persevere through challenges and disappointments. He has even been an editor of my writing at times. All my friends, from those in LA to those scattered across the country, have kept me grounded and reminded me to enjoy the journey and celebrate my accomplishments. Their friendship allowed me to be resilient through many moments of uncertainty as I completed this degree.

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Chowdhury S, Hossain ME, Ghosh PK, Ghosh S, Hossain MB, **Beard C**, Rahman M, Rahman MZ. The Pattern of Highly Pathogenic Avian Influenza H5N1 Outbreaks in South Asia. Trop Med Infect Dis. 2019 Nov 27;4(4):138. doi: 10.3390/tropicalmed4040138.

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1 Chapter 1: Introduction

1.1 Early History of COVID-19

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and the disease it causes, coronavirus disease 2019 (COVID-19) first emerged in the city of Wuhan in Hubei province in central China in December of 2019.[1] Local hospitals in Wuhan initially identified an outbreak of pneumonia cases of unknown origin, and on December 31, the local government in Wuhan reported that dozens of cases of this unknown pneumonia were being treated.[2,3] The disease spread outside of Hubei province in mid-January 2020.[4] Epidemiologic investigations initially tied the outbreak to the Huanan Seafood Wholesale Market in Wuhan, as two of the three earliest cases were directly linked to the market, as were 28% of all cases reported in December 2019.[5] Further research in late 2021 suggested that the initial human case was a vendor at that market whose symptoms began on December 1, 2019.[6]

The virus continued to spread within China and to other countries including Taiwan, Japan, Thailand, South Korea, and the United States.[3] On January 30, 2020, the World Health Organization declared the outbreak a Public Health Emergency of International Concern.[7] The WHO later declared the outbreak to be a pandemic on March 11, 2020.[8]

The first SARS-CoV-2 (at the time known as 2019-nCoV) infection in the U.S. was reported on January 20, 2020 in Washington state. The patient had recently returned from travel to Wuhan, China, leading the clinic to report the illness to the local and state health departments, who then notified the Centers for Disease Control and Prevention (CDC). The CDC then confirmed that the patient’s biological samples tested positive for SARS-CoV-2 via a real-time reverse-transcriptase—polymerase chain reaction (rRT-PCR) assay.[9] The patient had not visited the seafood market and did not recall having any contact with sick individuals during his travel to Wuhan, suggesting possible person-to-person asymptomatic transmission.[9] The U.S. Secretary of Health and Human Services declared a national public health emergency on January 31, 2020.[10]

The first reported death from COVID-19 in the U.S. occurred on February 29, also in Washington state, although later reporting from Santa Clara County, California revealed that there had been two COVID-19 deaths there on February 6 and February 17.[3] The first case of possible community spread in the U.S. was identified in California on February 26.[11] By April 26, 2020, there had been over 1 million confirmed COVID-19 cases in the U.S. The country surpassed 10 million cases on November 6, 2020. The largest surges in cases occurred in November 2020-January 2021 (driven by the original strain), August 2021-September 2021 (driven by the Delta variant), December 2021-February 2022 (driven by the Omicron variant), and May 2022-September 2022 (driven by several Omicron sublineages).[12]

Chinese researchers publicly shared the full genetic sequence of the novel virus on January 7, 2020, which allowed researchers around the world to begin research on developing diagnostics, vaccines, and therapeutics.[9] Several drugs and vaccines received Emergency Use Authorization (EUA) and, eventually, full approval from the U.S. Food and Drug Administration (FDA) throughout the pandemic response, including remdesivir, Paxlovid, the Pfizer/BioNTech vaccine, and the Moderna vaccine.[11]

On December 11, 2020, the FDA granted EUA for the COVID-19 vaccine developed by Pfizer/BioNTech for use in adults 18 years of age and older, allowing nationwide distribution and administration of vaccines to begin.[13] As of February 2023, bivalent booster doses of both the Pfizer/BioNTech vaccine and the Moderna vaccine have been authorized for administration to individuals who meet the eligibility criteria.[13] Both vaccines also have EUA for use in children ages 6 months and older.

Vaccination efforts in the U.S. were initially slow as production ramped up and as more individuals became eligible to receive a vaccine. As of February 23, 2023, 269,459,752 (81.2%) people in the U.S. have received at least one dose, 229.996,296 (69.3%) have completed their primary series of vaccine, and 53,350,658 (16.1%) have received a bivalent booster dose.[12]

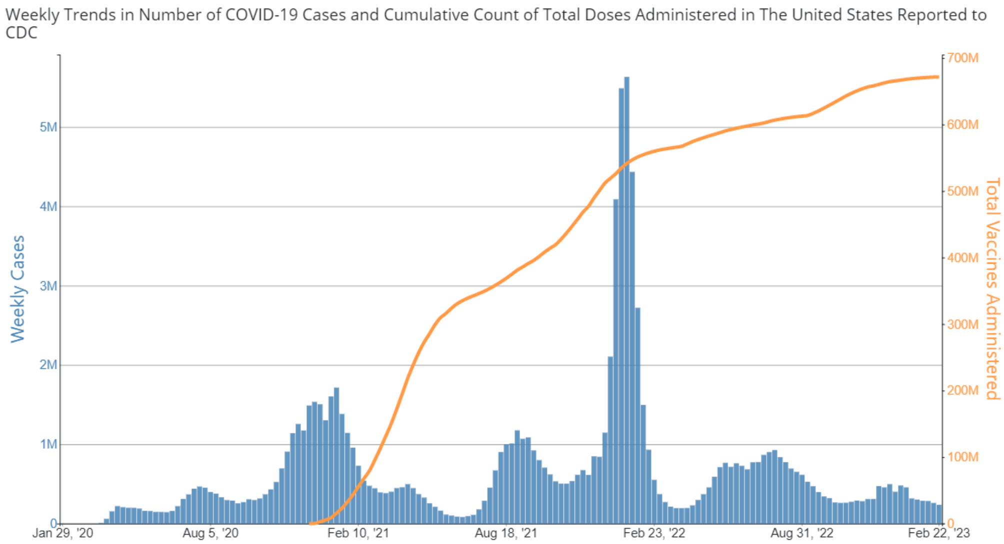

Figure 1-1: Epidemic curve of the COVID-19 epidemic in the United States, also showing total vaccines administered over time (source: CDC)

1.2 Epidemiology of COVID-19

Countries were able to quickly develop tests for SARS-CoV-2 and antibodies to the virus, but global supply chain disruptions limited access to testing supplies, which delayed the implementation of widespread diagnostic testing to aid in containment efforts.

Data from early cases in China and elsewhere produced estimates of the incubation period for the disease caused by the original strain of the virus of between 2 and 14 days, with a median of around 4-6 days.[1,4,14,15] This represents the amount of time between infection and symptom onset and is important to understand to allow for individual-level treatment. The estimated median incubation period for the Delta variant is 4 days, and the estimated median incubation period of the Omicron variant is 3-4 days.[16–18]

The latent period of a disease is the time between infection and when an individual becomes infectious and is important to understand for the prevention of disease transmission at the population level.[19] The estimated mean latent period for COVID-19 is between 2.9 and 5.5 days, with the majority of cases shedding virus before 10 days post-infection.[20,21]

A disease's infectious period is the window in which an infected individual is shedding virus and infectious. Prior to the emergence of the Delta and Omicron variants, the infectious period in most infected people lasted up to 10 days, with a mean of around 6.3 days.[21] For individuals infected with the Omicron subvariants, the period of greatest likelihood for transmission appears to be 1-2 days prior to symptom onset and 2-3 days after symptom onset.[22] However, there is ongoing discussion about how long infected individuals are truly contagious with the Omicron subvariants, which has been challenging to study given such varying levels of immunity in the population due to widespread natural infection, vaccination, and boosters.

The basic reproductive number (R_0) of a disease is the average number of secondary infections caused by an infected case in a completely susceptible population. The effective reproductive number (R_e) is the average number of secondary infections caused by an infected case under "real world" conditions (i.e., not in a completely susceptible population). The R_e of COVID-19 has been difficult to estimate throughout the pandemic due to conditions that vary by country and by community such as population density and public health policies. Most estimates of the R_0 value for the original strain of SARS-CoV-2 range from 2.0-3.5, although estimates have ranged from 1.5 to 6.49.[14,19,24–26] The R_0 number for the Delta variant of the virus is estimated around 5.0, and the R_0 for the Omicron variant is estimated around 9.5, although estimates vary slightly by subvariant as well.[27–30]

Table 1-1: Age-specific mortality rates for COVID-19 (source: Levin et al.)

Age Group	COVID-19 U.S. Mortality Rate[23]
0-4	0.3
5-17	0.1
18-29	Reference group
30-39	3.5
40-49	10
50-64	25
65-74	60
75-84	140
85+	350

Similarly, the infection fatality rate (IFR), or the proportion of all infections that result in death, of COVID-19 has been difficult to estimate due to a lack of widespread testing that made it difficult to understand the true burden of disease. Disease severity is highly correlated with age and overall health. A meta-analysis of studies with COVID-19 seroprevalence and fatality data from locations across the world estimated the age-specific infection fatality rates of COVID-19 to exponentially increase with age, a trend that is mirrored by the U.S. mortality rates shown in Table 1-1.[31]

Individuals with certain underlying health conditions are more susceptible to severe illness from a COVID-19 infection.[32] According to the CDC, the underlying health conditions that increase an individual's risk of severe disease from COVID-19 that are conclusively supported by current scientific evidence, are:

- Asthma
- Cancer
- Cerebrovascular disease
- Chronic kidney disease
- Chronic lung diseases (bronchiectasis, COPD, interstitial lung disease, pulmonary embolism, pulmonary hypertension)
- Chronic liver diseases (cirrhosis, non-alcoholic fatty liver disease, alcoholic liver disease, autoimmune hepatitis)
- Cystic fibrosis
- Diabetes mellitus, type 1
- Diabetes mellitus, type 2
- Disabilities, including Down syndrome
- Heart conditions (heart failure, coronary artery disease, cardiomyopathies)
- HIV
- Mental health conditions (mood disorders, including depression; schizophrenia spectrum disorders)
- Neurologic conditions (dementia)
- Obesity
- Physical inactivity
- Pregnancy and recent pregnancy
- Primary immunodeficiencies
- Smoking, current and former
- Solid organ or blood stem cell transplantation
- Tuberculosis
- Use of corticosteroids or other immunosuppressive medication

Understanding of the disease's mode of transmission has also evolved over time. Scientists initially suspected that the virus was only transmitted zoonotically, then found evidence of human-to-human transmission via a symptomatic infected individual, then found evidence of human-to-human transmission via an asymptomatic infected individual.[33]

Humans may be exposed to respiratory viral particles in three ways: 1) inhalation of very fine respiratory particles that have been aerosolized ("airborne"), 2) deposition of respiratory particles on exposed mucous membranes on the body via direct spray ("large-drop"), and 3) touching of exposed mucous membranes on the body after the skin comes into contact with a contaminated surface ("contact").[34,35] Scientific understanding of the risk of respiratory transmission of the virus has also evolved over time, but it is now understood that airborne transmission is a primary route of transmission of the disease between humans.[36,37] Direct transmission of the virus via large respiratory droplets dispersed over short distances is another mode of transmission, and fomite transmission of the virus via contaminated objects is possible but comparatively unlikely.[38] Vaccines and non-pharmaceutical interventions such as handwashing, masking, social distancing, and increased ventilation of indoor spaces are the primary tools used to prevent transmission of the virus.

The original reservoir of the virus continues to be an unknown. The fact that initial cases clustered around the Huanan South China Seafood Market, along with the knowledge that many coronaviruses circulate in animal reservoirs, led public health officials to initially suspect that the disease might be linked to a zoonotic spillover from a natural reservoir.[2] Several papers from 2022 provide strong epidemiologic and genetic evidence that SARS-CoV-2 first infected humans as a result of zoonotic spillover events at the market in Wuhan.[39–41] However, recent discourse from the U.S. federal government on the possibility that the virus accidentally escaped from a laboratory has highlighted that no researchers or agencies have yet reached conclusive findings.[42] Investigators from the World Health Organization and from national governments around the world continue to explore the possible origins of the pandemic.[43]

Bats were identified early on as one of the most probable animal reservoirs, as the genomic sequence of SARS-CoV-2 is 96.2% similar to a bat coronavirus known as RaTG13.[44] Research continues to investigate whether bats or another animal might have been the primary source of the pandemic.[5]

1.2.1 Global Context

As of February 26, 2023, there had been 757,264,511 total confirmed cases of COVID-19 globally and 6,850,594 total deaths. Cases have been confirmed in every country in the world except 2: Turkmenistan and the Democratic People's Republic of Korea.[45] Of the 6 WHO regions, Europe has the highest number of confirmed cases (272,814,122), followed by the Western Pacific (200,972,740) and the Americas (189,963,466), then South-East Asia, then Eastern Mediterranean, then Africa.[45]

1.2.2 United States Context

As of February 27, 2023, there had been 103,268,408 total reported cases of COVID-19 in the United States and 1,115,637 total deaths. Case rates per 100,000 since the beginning of the pandemic are relatively evenly distributed throughout the country, with Rhode Island, Kentucky, and North Dakota having the highest rates and American Samoa, the Marshall Islands, and Maryland having the lowest rates (Figure 1-2).[12] Racial and ethnic disparities in COVID-19 infections, hospitalizations, and deaths have existed throughout the country since the beginning of the pandemic, as these characteristics are linked to many determinants of health such as occupation, socioeconomic status, and access to health care. For example, African Americans have had a hospitalization rate that is 2.1 times higher and a death rate that is 1.6 times higher than those of white, non-Hispanic Americans. American Indians or Alaska Natives have a hospitalization rate that is 2.5 times higher and a death rate that is 2.2 times higher than that of white, non-Hispanic Americans.[23]

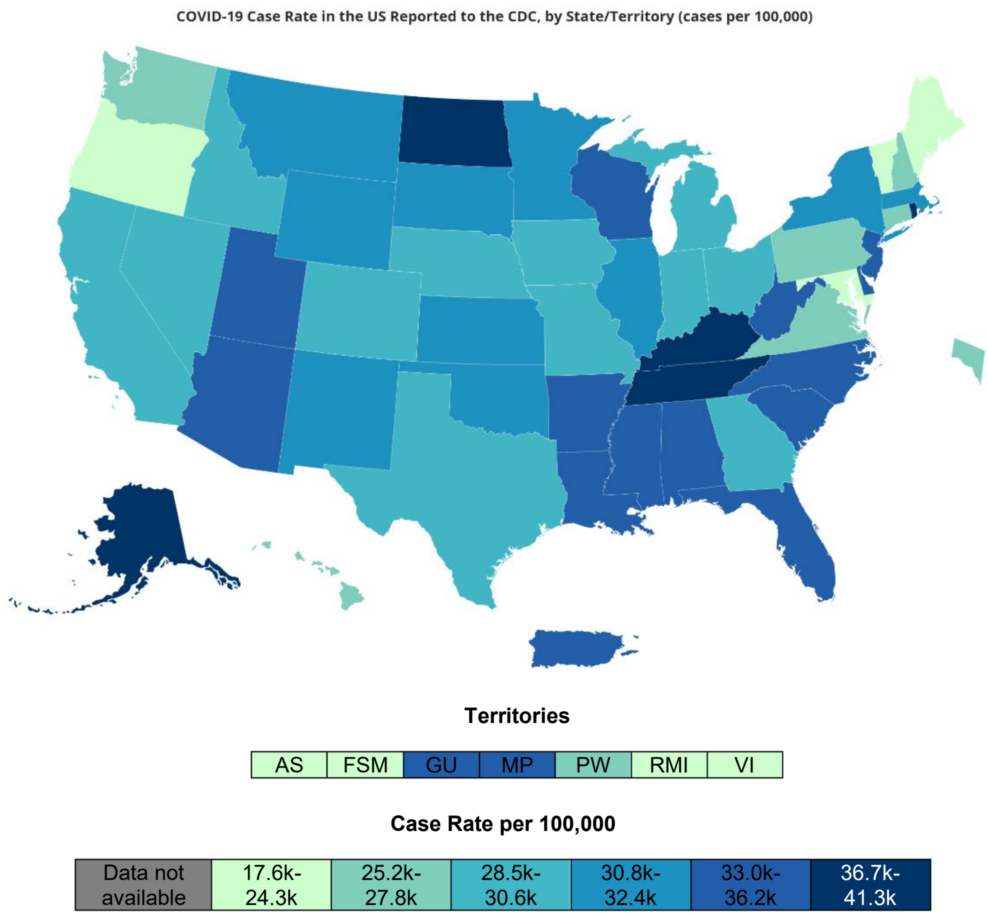

Figure 1-2: Map of COVID-19 case rate per 100,000 people in the U.S. as of Feb. 28, 2023 and since Jan. 21, 2020 (source: CDC)

1.3 Properties of SARS-CoV-2 Virus

SARS-CoV-2 is a novel enveloped RNA betacoronavirus, of the family Coronaviridae.[4] Coronaviruses are spherical, enveloped, single-stranded RNA viruses.[46] They are so named due to the spike proteins on their viral envelope which look like a crown, or “corona” in Latin.[4] RNA viruses are prone to genetic mutation, and since the emergence of the initial strain of SARS-CoV-2, many variants and subvariants have evolved.[47] As of February 28, 2023, the WHO is monitoring several subvariants of the Omicron variant of concern (see Table 1-2).[48] A variant of concern is a variant with genetic changes that has been demonstrated to have an increase in transmissibility, an increase in virulence, or have a negative impact on the effectiveness of public health prevention and control measures.[48]

To-date, there are seven known coronaviruses that infect humans: two alphacoronaviruses and five betacoronaviruses, which include SARS-CoV, Middle East Respiratory Syndrome (MERS), and SARS-CoV-2. Coronaviruses usually affect the respiratory, digestive, and/or nervous systems in humans and animals.[25]

Bats are the main viral reservoirs for coronaviruses, and current data suggests that SARS-CoV-2 may have originated in bats before crossing the species barrier to infect humans, possibly through an intermediate animal reservoir as well.[46]

Table 1-2: Variants of concern designated by the WHO (multiple sources)

WHO Label	Earliest documented samples[49]	Place first identified[48,50]	First case reported in U.S.[51]
Alpha	Feb 2020	United Kingdom (Sept 2020)	Colorado (Dec 29, 2020)
Beta	Feb 2020	South Africa (May 2020)	South Carolina (Jan 28, 2021)
Gamma	Apr 2020	Brazil (Nov 2020)	Minnesota (Jan 25, 2021)
Delta	Mar 2020	India (Oct 2020)	Mar 2021
Omicron (BA.1)	Jun 2020	South Africa and Botswana (Nov 2021)	California (Dec 1, 2021)
BA.2	Mar 2020	South Africa (Nov 2021)	Airport surveillance Dec 14, 2021[52]
BA.4	Jul 2020	South Africa (Jan 2022)[53]	March 2022[54]

However, coronaviruses have been identified around the world that infect many other animals, including dogs, cats, pigs, chicken, cows, and camels.[55] In addition to humans, SARS-CoV-2 has been found to infect minks, ferrets, otters, cats, dogs, big cats and primates.[56]

The four other human betacoronaviruses include OC43, HKU1, MERS-CoV, and SARS-CoV. People are commonly infected with OC43 and HKU1, which produce generally mild symptoms.[57] SARS-CoV was first identified in humans when it caused a severe outbreak in China and five other countries in 2002-2003.[25,58] MERS-CoV is not easily transmissible between humans and was first identified in humans in 2012; since then 27 countries have reported cases.[59] Both SARS-CoV and MERS-CoV emerged in the human population from zoonotic spillover events and have exhibited high pathogenicity and mortality in humans.[4]

The two human alphacoronaviruses, which also commonly infect humans around the world, are 229E and NL63, which also produce generally mild symptoms.[57]

1.4 Natural History of SARS-CoV-2

There are three stages of the natural history of SARS-CoV-2.[36] Phase 1 is the onset of disease and is when the host may begin to develop mild-to-moderate symptoms, although many infected individuals remain asymptomatic. The virus may be detected via RT-PCR during this phase. If the disease continues to progress, it moves to Phase 2, which is known as the pulmonary phase. Depending on the severity of the disease, a patient may begin to develop pneumonia-like symptoms during this phase. If the disease continues to progress from there, a patient enters Phase 3, the hyperinflammatory phase. This phase of the disease usually necessitates intensive care, and may result in death.

1.5 Clinical Features of COVID-19

The most prevalent symptoms of COVID-19 include fever, cough, sore throat, fatigue, myalgia, and difficulty breathing. Some infected individuals also experience gastrointestinal symptoms, loss of smell and/or taste, and headache. The severity of disease is highly associated with specific risk factors which include age, overall health, and presence of certain pre-existing conditions.[36]

Additionally, many patients continue to report symptoms after clearing a SARS-CoV-2 infection, a phenomenon known as "long COVID," or "post-acute COVID-19 syndrome." The phenomenon is defined as having persistent symptoms beyond 4 weeks from the onset of symptoms.[60] Some of the most common long-term symptoms include fatigue, difficulty breathing, cough, persistent loss of taste and/or smell, sleep difficulties, and cognitive disturbances, or "brain fog."[60] Studies have reported prevalence of long-term symptoms among patients ranging between 32.6% and

76% (among patients with COVID-19 who had been hospitalized).[61,62] The pathology of long COVID is still not well understood, making it difficult for healthcare providers to effectively treat patients to alleviate their symptoms.[63]

1.6 Mental Health Impacts of the COVID-19 Pandemic

The mental health impacts of the pandemic have increasingly become of interest to researchers, employers, and policy makers. The changes to daily routines and economic and social consequences of the pandemic and the global response to it have impacted the mental health of populations around the world, whether unemployed, working from home, or on the front lines of the response.

Surveys and systematic reviews conducted throughout the pandemic have revealed negative impacts on mental health across different subgroups of the U.S. and global populations.[64,65] An analysis of the Pew Research Center American Trends Panel survey completed between March 19-24, 2020 found that nearly 1 in 4 U.S. adults with no reported prior history of a mental condition were experiencing symptoms of psychological distress, which is higher than the population estimates for prevalence of symptoms of anxiety and depressive disorder the year prior.[66] The same analysis found associations between psychological distress and several risk factors, including female gender, use of social media to post about coronavirus, reported major changes to personal life as a result of the coronavirus, and perceptions that the coronavirus poses a threat to personal finances or the U.S. economy.[66] Another survey found that 41.1% of the adult population in the U.S. reported symptoms of anxiety and/or depressive disorder in January 2021.[67]

The negative mental health impacts of the pandemic have also been seen among children. A CDC study conducted between January 1 and October 17, 2020 found a 31% increase in mental health-related emergency department visits among children ages 12-17 and a 25% increase among children ages 5-11, compared to the same period in 2019.[68]

A systematic review of studies reporting changes in global prevalence of major depressive disorder and anxiety disorders during the COVID-19 pandemic found that increases in COVID-19 daily infection rates and reductions in human mobility were associated with increased prevalence of both major depressive disorder and anxiety disorders.[65] The same study also developed models to predict the increase in prevalence of these disorders in 2020 resulting from the COVID-19 pandemic, and estimated an additional 53.2 million (95% CI: 44.8-62.9) cases of major depressive disorder and an additional 76.2 million (95% CI: 64.3-90.6) cases of anxiety disorders.

Multiple surveys and studies found that females experienced greater mental health impacts from the pandemic than males, and younger age groups experienced greater mental health impacts compared to older age groups.[64–66] Other surveys have measured pessimism about the pandemic, policy attitudes, and changes in the mental health of Americans over time as they relate to other demographic factors besides gender and age. These surveys found that Black and Hispanic adults have been more likely than White adults to report symptoms of anxiety and/or depressive disorder during the pandemic.[67]

1.7 Impacts of the COVID-19 Pandemic on Essential Workers

The essential workforce is largely made up of individuals in occupations that put them in higher-risk settings and/or require some level of direct contact with other people. The U.S. Department of Homeland Security defines essential workers as those who conduct operations that are essential to continue critical infrastructure operations. Some of these critical infrastructure sectors include health care/public health, emergency services, food and agriculture, and government operations (which includes the education system).[69]

Data from the 2018 National Health Information Survey suggested that approximately 24% of all adult workers are at increased risk for severe illness for COVID-19 based on risk factors like age and pre-existing medical conditions.[70] Workers in particular industries have been found to be at higher risk of infection than others. In California, the public administration sector, which includes police and fire services, had a higher incidence of workplace outbreaks than other industries, and the health care and social assistance industry had a very high number of outbreak-associated cases.[71]

Health system workers and first responders have lived very different day-to-day lives throughout the pandemic than the general public. During the early phase of the pandemic, nosocomial, or healthcare-associated, transmission of the disease was a particular concern. During this phase, a large proportion of COVID-19 infections that occurred in the hospital setting occurred as a result of contact between clinicians and visitors with no or mild symptoms.[44]

One study found that during the COVID-19 pandemic, healthcare workers were three times more likely to contract COVID-19 than the general public.[72] Research finds high proportions of healthcare workers report some form of pandemic-related psychological impact such as symptoms of depression, anxiety, or stress.[72,73] Impacts to mental health outcomes within this population, including psychological distress, anxiety symptoms, depressive symptoms, burnout, and stress, have been driven by “concerns about contracting or transmitting virus, financial insecurity due to furloughs, separation from and worries about loved ones, a stressful work environment due to surge conditions with scarce supplies, traumatic experiences due to witnessing death of patients and colleagues, and other acute stressors.”[72] Many healthcare staff also reported feeling uniquely isolated because their family and friends were afraid to interact with them. These feelings of loneliness and isolation were particularly impactful to staff who were already struggling with their mental health.[72]

A cohort study in Arizona found that first responders had a higher risk of infection with COVID-19 compared to healthcare workers. However, the study also found that the risk of infection among other essential workers was not significantly different from that of healthcare workers, although incidence did vary across occupations within the ‘other essential workers’ group.[74] This group of other essential workers included individuals working in frontline education, childcare, social work, frontline retail, frontline hospitality, essential government operations, nonprofit jobs requiring in-person work, and essential infrastructure workers.

In frontline education settings, the risk of COVID-19 transmission is highly dependent on local transmission rates, types of variants circulating, the epidemiology of the disease among students and staff, vaccine coverage, and prevention measures that are put in place at schools.[75] However, multiple studies have shown that the risk of transmission in school settings is lower than, or similar to, levels of community transmission.[75] Additionally, several studies have suggested that in the context of schools, staff-staff transmission is more common than staff-student transmission, student-staff transmission, or student-student transmission.[75–77] Approximately one in four teachers are at higher risk of severe illness if infected with COVID-19.[78]

While healthcare workers and first responders will be a particular focus of this dissertation, many other sectors of the essential workforce have been similarly impacted in terms of increased risk of transmission, which may also have a negative impact on the mental health of workers in those sectors.

The Los Angeles County Department of Public Health tracked active outbreaks in non-residential settings, many of which are workplaces, throughout the pandemic. Between May 23, 2021 and January 29, 2022, which spanned the surge due to the Delta variant as well as much of the surge due to the original strain of the Omicron variant, there had been 3,073 active outbreaks in workplaces and food and retail stores.[79]

Few studies have examined COVID-19 impacts through an occupational lens in Los Angeles County specifically, and few studies have examined change in mental health longitudinally during the pandemic. This necessitates a longitudinal study of mental health outcomes in essential workers in order to better allow for comparisons and causal inference.[80] It also necessitates further study of COVID-19 infection risk and pandemic impacts through an occupational lens.

A fuller understanding of the complexity of the mental health impacts of the pandemic on healthcare workers, first responders, and workers from other essential sectors will take many more years, continued follow-up, and institutional recognition of the scope of the problem. This dissertation will aim to add to this understanding, with the goal of informing future institutional policies that may better protect both the physical and mental health of essential workers.

1.8 References

1. Guan, W. *et al.* Clinical Characteristics of Coronavirus Disease 2019 in China. *N. Engl. J. Med.* **382**, 1708–1720 (2020).

2. Li, Q. *et al.* Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus–Infected Pneumonia. *N. Engl. J. Med.* **382**, 1199–1207 (2020).

3. Taylor, D. B. A Timeline of the Coronavirus Pandemic. *The New York Times* (2021).

4. Helmy, Y. A. *et al.* The COVID-19 Pandemic: A Comprehensive Review of Taxonomy, Genetics, Epidemiology, Diagnosis, Treatment, and Control. *J. Clin. Med.* **9**, 1225 (2020).

5. Holmes, E. C. *et al.* The origins of SARS-CoV-2: A critical review. *Cell* **184**, 4848–4856 (2021).

6. Huang, C. *et al.* Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet* **395**, 497–506 (2020).

7. Timeline: WHO's COVID-19 response. *World Health Organization* https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline (2022).

8. WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020. *World Health Organization* https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020 (2020).

9. Holshue, M. L. *et al.* First Case of 2019 Novel Coronavirus in the United States. *N. Engl. J. Med.* **382**, 929–936 (2020).

10. Determination that a Public Health Emergency Exists. *U.S. Department of Health and Human Services Office of the Assistant Secretary for Preparedness and Response* https://www.phe.gov/emergency/news/healthactions/phe/Pages/2019-nCoV.aspx (2020).

11. Covid-19 Pandemic Timeline Fast Facts. *CNN* https://www.cnn.com/2021/08/09/health/covid-19-pandemic-timeline-fast-facts/index.html (2022).

12. COVID Data Tracker. *Centers for Disease Control and Prevention* https://covid.cdc.gov/covid-data-tracker (2023).

13. Emergency Use Authorization. *U.S. Food & Drug Administration* https://www.fda.gov/emergency-preparedness-and-response/mcm-legal-regulatory-and-policy-framework/emergency-use-authorization (2023).

14. Sanche, S. *et al.* High Contagiousness and Rapid Spread of Severe Acute Respiratory Syndrome Coronavirus 2. *Emerg. Infect. Dis.* **26**, 1470–1477 (2020).

15. Lauer, S. A. *et al.* The Incubation Period of Coronavirus Disease 2019 (COVID-19) From Publicly Reported Confirmed Cases: Estimation and Application. *Ann. Intern. Med.* **172**, 577–582 (2020).

16. Jansen, L. *et al.* Investigation of a SARS-CoV-2 B.1.1.529 (Omicron) Variant Cluster — Nebraska, November–December 2021. *MMWR Morb. Mortal. Wkly. Rep.* **70**, 1782–1784 (2021).

17. Song, J. S. *et al.* Serial Intervals and Household Transmission of SARS-CoV-2 Omicron Variant, South Korea, 2021. *Emerg. Infect. Dis.* **28**, 756–759 (2022).

18. Grant, R. *et al.* Impact of SARS-CoV-2 Delta variant on incubation, transmission settings and vaccine effectiveness: Results from a nationwide case-control study in France. *Lancet Reg. Health – Eur.* **13**, (2021).

19. Zhao, S. *et al.* Estimating the generation interval and inferring the latent period of COVID-19 from the contact tracing data. *Epidemics* **36**, (2021).

20. Xin, H. *et al.* Estimating the Latent Period of Coronavirus Disease 2019 (COVID-19). *Clin. Infect. Dis.* **74**, 1678–1681 (2022).

21. Wang, X. *et al.* Impact of Social Distancing Measures on Coronavirus Disease Healthcare Demand, Central Texas, USA. *Emerg. Infect. Dis.* **26**, 2361–2369 (2020).

22. Anthes, E. & Corum, J. Charting an Omicron Infection. *The New York Times* (2022).

23. Risk for COVID-19 Infection, Hospitalization, and Death By Race/Ethnicity. *Centers for Disease Control and Prevention* https://www.cdc.gov/coronavirus/2019-ncov/covid-data/investigations-discovery/hospitalization-death-by-race-ethnicity.html (2023).

24. Yu, C.-J. *et al.* Assessment of basic reproductive number for COVID-19 at global level: A meta-analysis. *Medicine (Baltimore)* **100**, (2021).

25. Yesudhas, D., Srivastava, A. & Gromiha, M. M. COVID-19 outbreak: history, mechanism, transmission, structural studies and therapeutics. *Infection* **49**, 199–213 (2020).

26. Liu, Y., Gayle, A. A., Wilder-Smith, A. & Rocklöv, J. The reproductive number of COVID-19 is higher compared to SARS coronavirus. *J. Travel Med.* **27**, (2020).

27. Liu, Y. & Rocklöv, J. The reproductive number of the Delta variant of SARS-CoV-2 is far higher compared to the ancestral SARS-CoV-2 virus. *J. Travel Med.* **28**, (2021).

28. Burki, T. K. Omicron variant and booster COVID-19 vaccines. *Lancet Respir. Med.* **10**, (2022).

29. Fan, Y. *et al.* SARS-CoV-2 Omicron variant: recent progress and future perspectives. *Signal Transduct. Target. Ther.* **7**, (2022).

30. Liu, Y. & Rocklöv, J. The effective reproductive number of the Omicron variant of SARS-CoV-2 is several times relative to Delta. *J. Travel Med.* **29**, (2022).

31. Levin, A. T. *et al.* Assessing the age specificity of infection fatality rates for COVID-19: systematic review, meta-analysis, and public policy implications. *Eur. J. Epidemiol.* **35**, 1123–1138 (2020).

32. Underlying Medical Conditions Associated with Higher Risk for Severe COVID-19: Information for Healthcare Professionals. *Centers for Disease Control and Prevention* https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-care/underlyingconditions.html (2023).

33. Chan, J. F.-W. *et al.* A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster. *The Lancet* **395**, 514–523 (2020).

34. Science Brief: SARS-CoV-2 Transmission. *Centers for Disease Control and Prevention* https://www.cdc.gov/coronavirus/2019-ncov/science/science-briefs/sars-cov-2-transmission.html (2021).

35. Bazant, M. Z. & Bush, J. W. M. A guideline to limit indoor airborne transmission of COVID-19. *Proc. Natl. Acad. Sci.* **118**, (2021).

36. dos Santos, W. G. Natural history of COVID-19 and current knowledge on treatment therapeutic options. *Biomed. Pharmacother.* **129**, (2020).

37. Greenhalgh, T. *et al.* Ten scientific reasons in support of airborne transmission of SARS-CoV-2. *The Lancet* **397**, 1603–1605 (2021).

38. COVID-19 transmission—up in the air. *Lancet Respir. Med.* **8**, 1159 (2020).

39. Worobey, M. *et al.* The Huanan market was the epicenter of SARS-CoV-2 emergence. Preprint at https://doi.org/10.5281/zenodo.6299115 (2022).

40. Pekar, J. E. *et al.* SARS-CoV-2 emergence very likely resulted from at least two zoonotic events. Preprint at https://doi.org/10.5281/zenodo.6291627 (2022).

41. Worobey, M. *et al.* The Huanan Seafood Wholesale Market in Wuhan was the early epicenter of the COVID-19 pandemic. *Science* **377**, 951–959 (2022).

42. Stolberg, S. G., Mueller, B. & Zimmer, C. The Origins of the Covid Pandemic: What We Know and Don’t Know. *The New York Times* (2023).

43. Maxmen, A. WHO names researchers to reboot outbreak origin investigations. *Nature* (2021) doi:10.1038/d41586-021-02813-y.

44. Wang, Y., Wang, Y., Chen, Y. & Qin, Q. Unique epidemiological and clinical features of the emerging 2019 novel coronavirus pneumonia (COVID-19) implicate special control measures. *J. Med. Virol.* **92**, 568–576 (2020).

45. WHO Coronavirus (COVID-19) Dashboard. *World Health Organization* https://covid19.who.int (2023).

46. Salata, C., Calistri, A., Parolin, C. & Palù, G. Coronaviruses: a paradigm of new emerging zoonotic diseases. *Pathog. Dis.* **77**, (2019).

47. Callaway, E. The coronavirus is mutating — does it matter? *Nature* **585**, 174–177 (2020).

48. Tracking SARS-CoV-2 variants. *World Health Organization* https://www.who.int/activities/tracking-SARS-CoV-2-variants (2023).

49. O'Toole, A., Scher, E. & Rambaut, A. Lineage List. *cov-lineages.org* https://cov-lineages.org/lineage_list.html.

50. Desingu, P. A., Nagarajan, K. & Dhama, K. Emergence of Omicron third lineage BA.3 and its importance. *J. Med. Virol.* **94**, 1808–1810 (2022).

51. CDC Museum COVID-19 Timeline. *Centers for Disease Control and Prevention* https://www.cdc.gov/museum/timeline/covid19.html (2023).

52. Anthes, E. A C.D.C. airport surveillance program found the earliest known U.S. cases of Omicron subvariants. *The New York Times* (2022).

53. SARS-CoV-2 variants of concern and variants under investigation in England: Technical briefing 40. (2022).

54. Lin II, R.-G. & Money, L. New coronavirus variants emerge: BA.4, BA.5 likely reinfecting Omicron survivors. *Los Angeles Times* (2022).

55. Alluwaimi, A. M., Alshubaith, I. H., Al-Ali, A. M. & Abohelaika, S. The Coronaviruses of Animals and Birds: Their Zoonosis, Vaccines, and Models for SARS-CoV and SARS-CoV2. *Front. Vet. Sci.* **7**, (2020).

56. Cases of SARS-CoV-2 in Animals in the United States. *U.S. Department of Agriculture Animal and Plant Health Inspection Service* https://www.aphis.usda.gov/aphis/dashboards/tableau/sars-dashboard (2023).

57. Human Coronavirus Types. *Centers for Disease Control and Prevention* https://www.cdc.gov/coronavirus/types.html (2020).

58. SARS outbreak contained worldwide. *World Health Organization* https://www.who.int/news/item/05-07-2003-sars-outbreak-contained-worldwide (2003).

59. Middle East respiratory syndrome coronavirus (MERS-CoV). *World Health Organization* https://www.who.int/news-room/fact-sheets/detail/middle-east-respiratory-syndrome-coronavirus-(mers-cov) (2022).

60. Nalbandian, A. *et al.* Post-acute COVID-19 syndrome. *Nat. Med.* **27**, 601–615 (2021).

61. Huang, C. *et al.* 6-month consequences of COVID-19 in patients discharged from hospital: a cohort study. *The Lancet* **397**, 220–232 (2021).

62. Chopra, V., Flanders, S. A., O'Malley, M., Malani, A. N. & Prescott, H. C. Sixty-Day Outcomes Among Patients Hospitalized With COVID-19. *Ann. Intern. Med.* **174**, 576–578 (2021).

63. Brown, K., Yahyouche, A., Haroon, S., Camaradou, J. & Turner, G. Long COVID and self-management. *The Lancet* **399**, 355 (2022).

64. Lopes, L., Kearney, A., Kirzinger, A., Hamel, L. & Brodie, M. KFF Health Tracking Poll – December 2020: COVID-19 and Biden's Health Care Agenda. *KFF* https://www.kff.org/coronavirus-covid-19/report/kff-health-tracking-poll-december-2020/ (2020).

65. Santomauro, D. F. *et al.* Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories in 2020 due to the COVID-19 pandemic. *The Lancet* **398**, 1700–1712 (2021).

66. Holingue, C. *et al.* Mental Distress during the COVID-19 Pandemic among US Adults without a Pre-existing Mental Health Condition: Findings from American Trend Panel Survey. *Prev. Med.* **139**, (2020).

67. Panchal, N., Saunders, H., Rudowitz, R. & Cox, C. The Implications of COVID-19 for Mental Health and Substance Use. *KFF* https://www.kff.org/coronavirus-covid-19/issue-brief/the-implications-of-covid-19-for-mental-health-and-substance-use/ (2023).

68. Leeb, R. T. *et al.* Mental Health–Related Emergency Department Visits Among Children Aged 18 Years During the COVID-19 Pandemic — United States, January 1–October 17, 2020. *MMWR Morb. Mortal. Wkly. Rep.* **69**, 1675–1680 (2020).

69. Easterly, J. Guidance on the Essential Critical Infrastructure Workforce: Ensuring Community and National Resilience in COVID-19 Response. (2021).

70. Claxton, G. *et al.* Almost One in Four Adult Workers is Vulnerable to Severe Illness from COVID-19. *KFF* https://www.kff.org/coronavirus-covid-19/issue-brief/almost-one-in-four-adult-workers-is-vulnerable-to-severe-illness-from-covid-19/ (2020).

71. Heinzerling, A. *et al.* Workplaces Most Affected by COVID-19 Outbreaks in California, January 2020–August 2021. *Am. J. Public Health* **112**, 1180–1190 (2022).

72. Goodwin Veenema, T. *et al. Mental Health and Social Support for Healthcare and Hospital Workers During the COVID-19 Pandemic*. https://www.centerforhealthsecurity.org/our-work/pubs_archive/pubs-pdfs/2021/20210923-C19-mental-health.pdf (2021).

73. Lai, J. *et al.* Factors Associated With Mental Health Outcomes Among Health Care Workers Exposed to Coronavirus Disease 2019. *JAMA Netw. Open* **3**, e203976 (2020).

74. Ellingson, K. D. *et al.* Incidence of SARS-CoV-2 Infection Among Health Care Personnel, First Responders, and Other Essential Workers During a Prevaccination COVID-19 Surge in Arizona. *JAMA Health Forum* **2**, e213318 (2021).

75. Science Brief: Transmission of SARS-CoV-2 in K-12 Schools and Early Care and Education Programs - Updated. *Centers for Disease Control and Prevention* https://www.cdc.gov/coronavirus/2019-ncov/science/science-briefs/transmission_k_12_schools.html (2021).

76. Yung, C. F. *et al.* Novel Coronavirus 2019 Transmission Risk in Educational Settings. *Clin. Infect. Dis.* **72**, 1055–1058 (2021).

77. Ismail, S. A., Saliba, V., Bernal, J. L., Ramsay, M. E. & Ladhani, S. N. SARS-CoV-2 infection and transmission in educational settings: a prospective, cross-sectional analysis of infection clusters and outbreaks in England. *Lancet Infect. Dis.* **21**, 344–353 (2021).

78. Claxton, G. *et al.* How Many Teachers Are at Risk of Serious Illness If Infected with Coronavirus? *KFF* https://www.kff.org/coronavirus-covid-19/issue-brief/how-many-teachers-are-at-risk-of-serious-illness-if-infected-with-coronavirus/ (2020).

79. Reopening LA County Dashboard. *Los Angeles County Department of Public Health* http://publichealth.lacounty.gov/media/coronavirus/data/reopening-dashboard.htm (2022).

80. Barzilay, R. *et al.* Resilience, COVID-19-related stress, anxiety and depression during the pandemic in a large population enriched for healthcare providers. *Transl. Psychiatry* **10**, 291 (2020).

2 Aim 1 – Ecologic exploration of community occupational structure and COVID-19 impact in Los Angeles County, CA

2.1 Abstract

Background: Occupation can be an important predictor of disease risk. Over 20% of the workforce in Los Angeles County works in healthcare, education, first response, or food service. Each of these four occupational sectors has a different COVID-19 risk profile, but how the pandemic has impacted workers in these different sectors is not fully understood.

Methods: Publicly available data from Los Angeles County Department of Public Health COVID-19 Data Dashboard was used to measure the impact of COVID-19 at the community level. Data from the U.S. Census American Community Survey was used to create measures of the proportions of the civilian employed population 16 years old and older in each community in LA County working in education, healthcare, first response, or food service. Visualizations and regressions were used to investigate associations between these measures at the ecologic level.

Results: Communities in central, east, and north LA County had higher COVID-19 impact scores throughout the study period. Among all communities in the study sample, COVID-19 impact scores were highest in December 2020-Feburary 2021 and January 2021-February 2022. A higher proportion of the workforce in a community working in healthcare or in education was associated with a decrease in COVID-19 impact at the community level, and a higher proportion of the workforce in a community working in first response or food service was associated with an increase in COVID-19 impact at the community level.

Conclusions: Community employment share in the healthcare, first response, education, or food service industries is associated with COVID-19 impact on an ecological level.

Keywords: COVID-19, Los Angeles, occupation, healthcare, education, first response, food service, ecologic

2.2 Introduction

Employment is considered a social determinant of health, or a non-medical factor that influences an individual's health outcomes.[1] Not only can the attributes of specific types of work contribute to disease risk and affect health outcomes, but employment is closely linked with other social determinants of health such as socioeconomic status and access to healthcare. The risk of infectious disease in specific occupations has been well documented.[2] Previous research has also demonstrated associations between community occupational structure, defined as "the set of occupations which exist in a community," and heart disease mortality.[3,4] Studies often measure community occupational structure using "employment share," or the percent of the workforce in a given community that holds specific types of employment.

The COVID-19 pandemic led state and local governments around the United States to issue stay-at-home orders to reduce transmission of the SARS-CoV-2 virus and protect the healthcare system. With these changes, occupation-related risks of COVID-19 shifted as some workers continued to report to work in person and others either worked remotely or lost their jobs. As personal protective equipment (PPE), diagnostic tests, and vaccines became available and as the economy reopened over time, these occupation-related risks continued to change.

From January 1, 2020 to August 31, 2021, a study in California found that among all reported COVID-19 outbreaks in the state, the occupational sectors that accounted for the largest proportions of outbreaks were the health care and social assistance sector, the retail trade sector, the manufacturing sector, and the accommodation and food services sector.[5] However, the industry sector with the highest *incidence* of reported SARS-CoV-2 outbreaks, defined as the number of outbreaks per 1,000 establishments, was public administration, which includes public safety workplaces such as police and fire.[5] Behind public administration, utilities, manufacturing, and educational services are the industry sectors that had the next highest incidences of reported SARS-CoV-2 outbreaks.[5] Other studies have found that incidence of COVID-19 infection among workers has varied across occupations.[6]

Los Angeles County is the most populous county in the United States, with an estimated 10.1 million residents in 2019.[7] As of January 13, 2023, Los Angeles County had the most total COVID-19 cases and the second most total COVID-19 deaths of all counties in the country.[8] The Los Angeles County Department of Public Health (LACDPH) has tracked active COVID-19 outbreaks in workplaces throughout the pandemic, but to-date there has been little research examining associations between community occupational structure and COVID-19 risk and impacts in Los Angeles County.

This analysis examines the association between community occupational structure, measured as employment share in four specific occupational sectors across LA County, and COVID-19 impact at the community level across the county. The four occupational sectors included in this analysis are healthcare, education, first response, and food service. This ecologic study will describe the impacts of COVID-19 at the community level in LA County throughout the COVID-19 pandemic, examine how those impacts may be related to community occupational structure, and provide context to future research about how occupation has been related to COVID-19 impacts in LA County.

2.3 Methods

2.3.1 Study Design and Data Sources

This is an ecologic study using publicly available data at the community level from two different sources: the U.S. Census American Community Survey (ACS) and the LACDPH COVID-19 Data Dashboard.

The ACS is an annual household survey that uses a series of monthly samples to estimate demographic, social, economic, and housing data about the U.S. population. It provides 1- or 5-year estimates for all areas of the country at various geographic levels such as counties, places, and census tracts.[9] Each year, household units and group quarters in each of the counties and county equivalents in the U.S. are sampled and then surveyed or interviewed to collect the data that produces the ACS estimates.[9] For the 2015-2019 ACS 5-year estimates, 266,482 of 440,299 selected household units in Los Angeles County completed the survey or interview. Sampling of group quarters residents is done at the state, not county, level, so for the 2019 ACS 5-year estimates, 73,855 of 90,943 sampled group quarters residents in the state of California completed the survey or interview.[10]

Throughout the COVID-19 pandemic, LACDPH has collected COVID-19 surveillance data on the population of LA County and made much of that data publicly available online.[11] This data includes case counts and infection rates over 7- and 14-day periods, number of hospitalizations and hospitalization rates over 14-day periods, number of deaths and death rates over 7- and 14-day periods, and cumulative number of diagnostic tests and testing rates by “City/Community” in the county. LACDPH uses 2018 and 2019 population estimates from the U.S. Census Population Estimates Program (PEP) population estimates for these “Cities/Communities”. The PEP estimates are available at a geographic level referred to as “Places” in U.S. Census data. For this analysis, the “community” level is measured at this “Places” level used by the U.S. Census. The U.S. Census defines “Places” as either Incorporated Places or Census Designated Places, which are the statistical counterparts of Incorporated Places used for areas that have not been legally incorporated.[12] “Places” in Los Angeles County were matched up with the “City/Community” level used by the LACDPH to produce the sample used in this study. There were 86 “Places” (all Incorporated Places) that matched up with a “City/Community.” We refer to these geographic areas as simply “communities” in the analysis.

The available data from LACDPH dates back to March 1, 2020 and continues to the present, but this analysis uses data between March 2020 and March 2022.

2.3.2 Measures of Interest

The *tidycensus* package in R was used to download demographic data at the "Place" level from the U.S. Census Bureau website.[13] The main covariates of interest are proportions of residents in each community that work in the four specific occupational sectors, each of which is measured by the ACS variables listed (and defined) below.

Education workers:

1. "Educational instruction, and library occupations" (listed under Management, business, science, and arts occupations)

Healthcare workers:

2. "Health diagnosing and treating practitioners and other technical occupations" (listed under Management, business, science, and arts occupations)
3. "Health technologists and technicians" (listed under Management, business, science, and arts occupations)
4. "Healthcare support occupations" (listed under Service occupations)

First responders:

5. "Firefighting and prevention, and other protective service workers including supervisors" (listed under Service occupations)

Food service workers:

6. "Food preparation and serving related occupations" (listed under Service occupations)

Each of these four occupational categories is measured as a proportion of the civilian employed population 16 years of age and older, also called an employment share.

In addition to occupation, other covariates that were taken from the ACS for inclusion in the analysis are sociodemographic characteristics at the ecological level. These include the proportion of residents in each community that are male, the proportion of residents that are Hispanic or Latino, the proportion of residents who are 65 years of age or older, the proportion of residents with an undergraduate degree or higher, and the median household income in each community.

There are four outcomes of interest in the analysis: adjusted 14-day case rate, adjusted 14-day hospitalization rate, adjusted 14-day death rate, and overall COVID-19 impact at the community level. All adjusted 14-day rates came from the LACDPH data. Each of these rates was averaged over the two years to create "cumulative" rates for each community. Each rate was also averaged over each month from March 2020-March 2022 to create monthly measures for each community included in the sample.

In order to create a measure of overall COVID-19 impact, each of the 86 communities in the sample was assigned three ranks for each month and for the entire study period: one for its relative case rate, one for its relative hospitalization rate, and one for its relative death rate. These three ranks were then combined into one measure, capturing disease extent and disease severity, to represent the overall impact of COVID-19 on each community. That final measure thus functioned as an "impact score" for each community during each month and across the entire study period. When the ranks were combined, case rate was down-weighted and death rate was up-weighted so the resulting score was more heavily influenced by hospitalization rate and death rate than by case rate. The resulting scores ranged from 3.5 to 294.5, although they had a hypothetical range of 3.5 to 301. Previous studies have used similar indices to show COVID-19 impact on specific industries or communities.[5,14,15]

2.3.3 Data Analysis

First, descriptive statistics were generated for each of the communities in the sample, showing counts and percentages for categorical variables and median and margin of error for the one continuous variable. Then, a series of maps was created using the geographic data available through the Census. One set of maps shows the proportion of the civilian employed population aged16 years and older working in each of the four occupations of interest (education, healthcare, food service, and first response) by community with available data. The other set of maps shows snapshots of the calculated COVID-19 impact score for each available community in LA County on average throughout the study period as well as for the months of January 2021, August 2021, and January 2022. January 2021 is of particular interest since it represents a time before vaccines were widely available to many essential workers outside of healthcare, and because it marked the beginning of a surge of cases in LA County. August 2021 is of interest because the Delta variant was surging in LA County, and January 2022 is of interest because of the Omicron variant surge that took place in the county.

To allow further visual exploration of the longitudinal data, a line graph depicting the average monthly COVID-19 impact scores across all 86 communities over time was created.

Finally, a series of univariate regression models was used to explore associations between demographic covariates, proportion of workers in each of the occupations of interest, and the four outcome measures over the study period at the community level. Overall impact score, average adjusted 14-day case rate over the entire study period, average adjusted 14-day hospitalization rate over the entire study period, and average adjusted 14-day death rate over the entire study period were each examined as outcomes in separate models. For each outcome, there was one model for each of the nine predictors, resulting in nine univariate models per outcome, and 36 total univariate models across all four outcome variables. [1]

Data management and data analyses were performed in R/RStudio, using the *tidycensus* package.[16]

[1] Covariates in all models were standardized by subtracting the variable mean and dividing by the standard deviation, so the resulting beta coefficients correspond to an increase of one standard deviation for each variable.

2.4 Results

An estimated total of 10,081,570 people lived in Los Angeles County as of the 2019 ACS. 49.3% (n=4,969,382) of the county was male, 48.5% (n=4,888.434) were Hispanic or Latino, and 13.3% (n=1,335,978) residents were 65 years of age or older (Table 2-1). Sixty-seven and a half percent (n=4,645,816) of those ages 25 and older had completed some college or less, 21.2% (n=1,460,862) had completed a bachelor's degree, and 11.3% (n=780,217) had completed an advanced degree.

The maps in Figure 2-1 depicting COVID-19 impact scores by place show that scores varied widely month-to-month and averaged throughout the study period. Communities in north, central, and east Los Angeles had higher COVID-19 impact scores across these cutpoints as well as averaged throughout the study period.

The five communities in LA County with the highest COVID-19 impact scores from measures averaged throughout the study period were 1) City of Industry, 2) City of Lynwood, 3) City of Maywood, 4) City of Maywood, and 5) City of Bell. The five highest monthly COVID-19 impact scores from communities in the county all occurred in January or February 2021.

As shown in Figure 2-1 and Figure 2-2, the largest COVID-19 impact scores were generated in December 2020-February 2021 and in December 2021-February 2022. The pattern of impact scores over time between March 2020 and March 2022 mirrors the epidemic curve of the pandemic in Los Angeles County which fluctuated as new variants and subvariants of the virus emerged over time and caused different peaks and troughs in case rates.

Figure 2-3 shows the community occupational structure of Los Angeles County with respect to the occupational sectors of healthcare, first response, education, and food service. Each of the four maps in this figure uses a different scale, as the four represented occupational sectors employ different proportions of the overall working-age county population (see Table 2-1). Overall, 20.9% of the county's working-age population works in one of these four occupations.

Communities with the highest proportions of first responders are in the north and central parts of the county, and communities with the highest proportions of education workers are found in the east part of the county. Communities with the highest proportions of healthcare workers or food service workers do not show a clear geographic pattern.

Table 2-1: Demographic characteristics of LA County residents (source: U.S. Census 2015-2019 American Community Survey)

		N	%
Total		10,081,570	100.0%
Age			
	Under 18	2,214,760	22.0%
	18-39	3,310,310	32.8%
	40-64	3,220,522	31.9%
	65+	1,335,978	13.3%
Sex			
	Female	5,112,188	50.7%
	Male	4,969,382	49.3%
Race			
	AI/AN (alone)	73,393	0.7%
	Asian (alone)	1,473,221	14.6%
	Black (alone)	820,478	8.1%
	NH/PI (alone)	27,720	0.3%
	White (alone)	5,168,443	51.3%
	Other (alone)	2,115,548	21.0%
	2+	402,767	4.0%
	2 (with 'Other')	115,953	1.2%
	2 (without 'Other') and 3+	286,814	2.8%
Ethnicity			
	Hispanic/Latino	4,888,434	48.5%
	Non-Hispanic/Latino	5,193,136	51.5%
Educational Attainment for Population 25+ years			
	Some college or less	4,645,816	67.5%
	Bachelor's Degree	1,460,862	21.2%
	Advanced Degree	780,217	11.3%
Occupation for Civilian Employed Population 16+ years			
	Education	254,383	5.2%
	Healthcare	420,757	8.5%
	Food Service	287,406	5.8%
	First Response	66,858	1.4%
	^All 4 combined	1,029,404	20.9%
		Median	Margin of Error
Household Income		$ 68,044.00	347.0

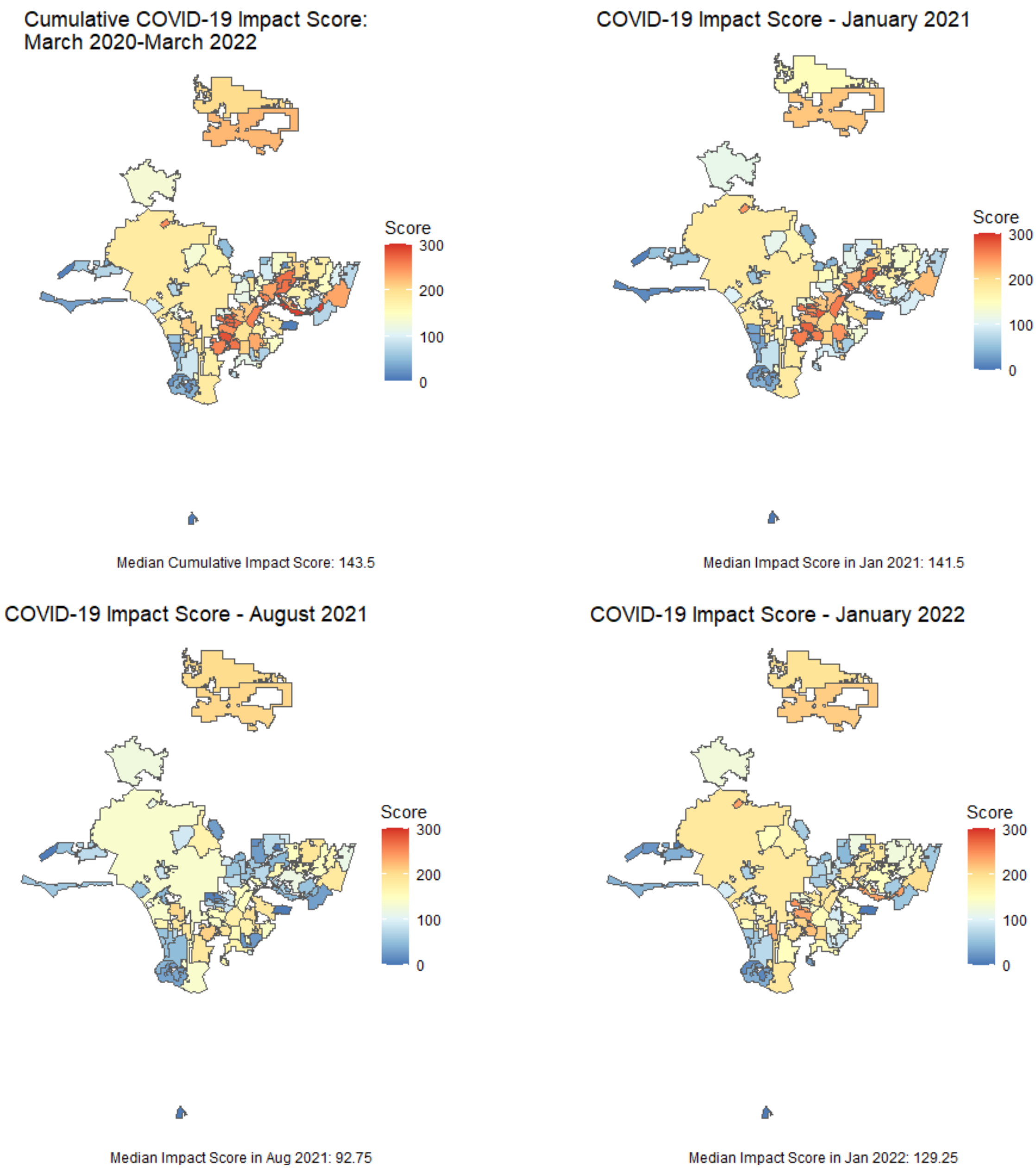

Figure 2-1: Top-left – map of the average COVID-19 impact at the community level for the entire study period; top-right – map of the COVID-19 impact at the community level in the month of January 2021; bottom-left – map of the COVID-19 impact at the community level in the month of August 2021; bottom-right – map of the COVID-19 impact at the community level in the month of January 2022 (source: U.S. Census 2015-2019 American Community Survey)

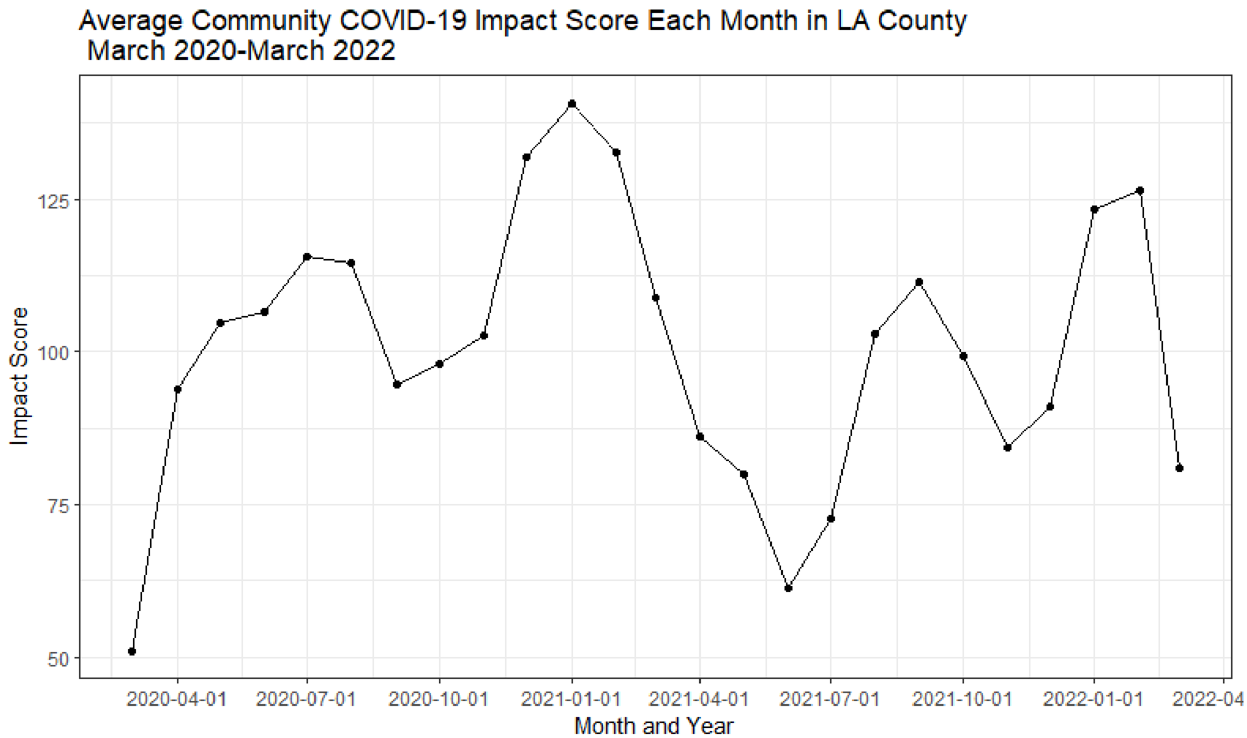

Figure 2-2: Line graph of the average monthly COVID-19 impact score across all 86 communities included in the study population over time

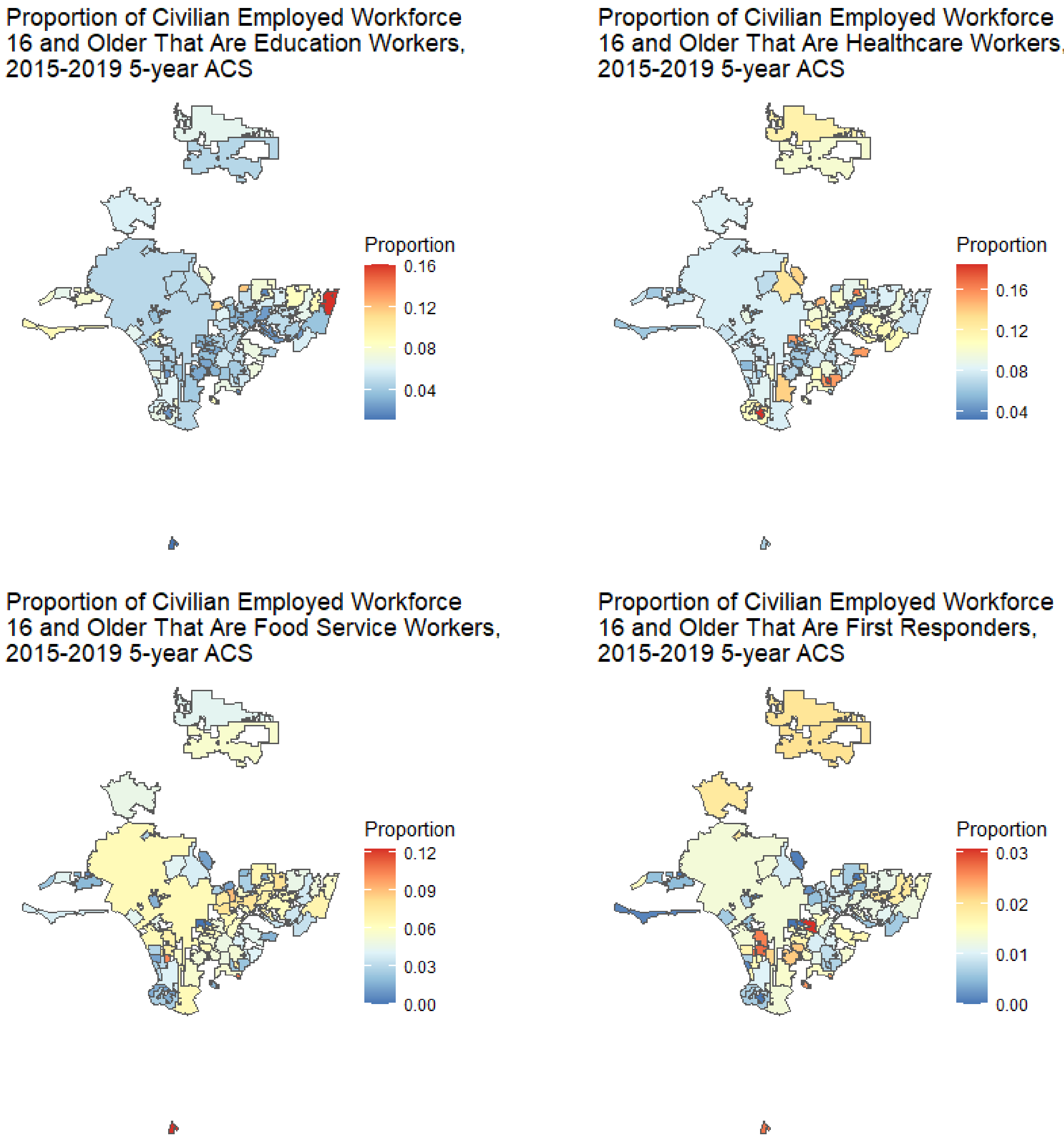

Figure 2-3: Maps of the proportions of the civilian employed workforce 16 years of age and older in each city/community that work in education, healthcare, food service, and first response (note that the scales are different)

The regression models (Table 2-2) used outcomes that resulted from averaging over the entire study period from March 2020-March 2022. Across all four outcomes, a higher proportion of a community age 65 and older was associated with a reduction in overall impact score, and with a reduction in incidence rate ratio (IRR) of infection, of hospitalization, and of death. A higher proportion of a community with a bachelor’s degree or higher was also associated with a reduction in overall impact score, a reduction in the IRR of infection, a reduction in the IRR of hospitalization, and a reduction in the IRR of death. A higher median household income in a community was also associated with reductions in all four outcomes.

A higher proportion of Hispanic or Latino individuals in a community was associated with an increase in impact score, with an increase in the IRR of infection, with an increase in the IRR of hospitalization, and with an increase in the IRR of death in two. A higher proportion of males in a community was associated with a decrease in the IRR of infection, an increase in the IRR of hospitalization, and an increase in the IRR of death. The proportion of males in a community was not associated with overall COVID-19 impact score.

A higher proportion of the civilian workforce in a community working in healthcare was associated with a slight increase in the IRR of infection (β=0.03, $p<0.001$), but with a decrease in impact score (β=-24.49, $p=0.01$) and a decrease in the IRRs of hospitalization (β=-0.17, $p<0.001$) and of death (β=-0.16, $p=0.002$). A higher proportion of first responders in a community was associated with an increase in impact score (β=29.77, $p=0.001$), an increase in the IRR of hospitalization (β=0.18, $p<0.001$) and an increase in the IRR of death (β=0.15, $p<0.001$). There was a slight negative association with case rate in the univariate first response model (β=-0.03, $p<0.001$). A higher proportion of education workers in a community was associated with a reduction in the IRR for infection (β=-0.21, $p<0.001$), hospitalization (β=-0.31, $p<0.001$), and death (β=-0.28, $p<0.001$) and with a reduction in impact score (β=-33.75, $p<0.001$). A higher proportion of food service workers in a community was associated with an increase in the IRR for hospitalization (β=0.22, p<0.001) and death (β=0.27, p<0.001), and with an increase in impact score (β=43.19, p<0.001). However, similar to employment share of first responders, a higher proportion of food services workers in a community was also associated with a slight decrease in the IRR of infection (β=-0.03, p<0.001).

Table 2-2: Unadjusted regression models examining associations between ecologic-level covariates, the proportion of a community's workforce working in healthcare, first response, education, and food service, and 4 different measures of COVID-19 impact between Mar 2020-Mar 2022, LA County

		Impact Score[a]		Case Rate[b]		Hospitalization Rate[b]		Death Rate[b]	
Unadjusted Model		β	p-value	β	p-value	β	p-value	β	p-value
Proportion 65+		**-59.71**	<0.001	**-0.45**	<0.001	**-0.49**	<0.001	**-0.46**	<0.001
Proportion Male		12.56	0.17	**-0.20**	<0.001	**0.08**	<0.001	**0.11**	0.02
Proportion Hispanic or Latino		**71.67**	<0.001	**0.34**	<0.001	**0.48**	<0.001	**0.45**	<0.001
Proportion with a Bachelor's Degree or higher		**-73.71**	<0.001	**-0.38**	<0.001	**-0.59**	<0.001	**-0.56**	<0.001
Median Household Income		**-63.16**	<0.001	**-0.30**	<0.001	**-0.65**	<0.001	**-0.61**	<0.001
Occupation for Civilian Employed Population 16+ years									
	Education	**-33.75**	<0.001	**-0.21**	<0.001	**-0.31**	<0.001	**-0.28**	<0.001
	Healthcare	**-24.49**	0.01	**0.03**	<0.001	**-0.17**	<0.001	**-0.16**	0.002
	Food Service	**43.19**	<0.001	**-0.03**	<0.001	**0.22**	<0.001	**0.27**	<0.001
	First Response	**29.77**	0.001	**-0.03**	<0.001	**0.18**	<0.001	**0.15**	0.001

[a]Linear regression (n=86)
[b]Poisson regression (n=86)

2.5 Discussion

Several outcomes and occupations of interest were included in this analysis to identify differences in associations that might align with the different COVID-19 risk profiles of these occupations. For example, most education workers in LA County worked from home until at least April 2021, by which time vaccines had been made available to these workers.[17] This may have resulted in reduced exposure for these workers that is reflected in the association with a decrease in impact score among communities with a higher proportion of education workers. Healthcare workers had greater access to COVID-19 testing than most other occupational groups, which may have resulted in an increase in early case identification and therefore a reduction in hospitalizations and deaths among this group, which is also reflected in the results. The healthcare sector also had greater access to high-quality masks and other PPE than most other sectors, and adherence to interventions like testing and masking was high due to both education/training and mandates. Healthcare workplaces also had advanced environmental controls in place such as HEPA filters. Comparatively, many food service workers did not have access to high-quality masks and worked in poorly-ventilated areas.

Averaging rates over the entire study period for the regression models may have attenuated some expected trends due to changes over time as communities dealt with variant-caused surges and as vaccination- and infection-derived immunity became more common among the population. Vaccination rates vary across some demographic categories, such as race/ethnicity and age, and these differences may have worked to produce some unexpected associations in the regression models, such as a higher proportion of a community over the age of 65 being associated with a decrease in the IRRs for infection, hospitalization, and death.[18]

This may also be attributable to the fact that many of the communities with larger proportions of their populations age 65 and older also had higher median incomes and may have therefore had better access to healthcare or other protective socioeconomic factors. It is also important to note that older individuals were eligible for vaccination before younger individuals, and may have better adhered to social distancing recommendations and stay-at-home orders than due to increased risk.

To better understand how socioeconomic factors were related to impacts of the pandemic on individual households, the U.S. Census launched the Household Pulse Survey during the pandemic.[19] While data from the decennial census and ACS are not specifically targeted at COVID-19 or even any specific health outcomes, this study demonstrates the value of incorporating many of these data sources as “quick response” data that can be combined with state and local health department data to allow for analyses similar to the Household Pulse Survey. During an infectious disease outbreak response, rapidly available data is a critical need as surveillance systems at the local, state, federal, and tribal/territorial levels continue to evolve.[20]

The construction and use of a measure of COVID-19 community impact in this study offers a comparison to the COVID-19 Community Levels used by the Centers for Disease Control (CDC). The system for determining which CDC COVID-19 Community Level a jurisdiction falls within is essentially a decision tree requiring data about the local impacts of the disease on the healthcare system and about new cases of COVID-19.[21] There is value in refining a measure of COVID-19 impact such as that used in this study to allow for more straightforward analyses and comparisons across geographic areas. As is briefly discussed in the limitations section, it is challenging to construct a score that is simultaneously comprehensive, meaningful, and easily interpretable. Such a measure will be useful as COVID progresses toward a level of endemicity in the U.S.

There are many other examples of indices constructed for understanding individual and community vulnerability that can inform further refinement of such a measure. Some of these include the Social Vulnerability Index,[22] the Covid-19 Community Vulnerability Index (CCVI),[23] the Area Deprivation Index (ADI),[24] and the Minority Health-Social Vulnerability Index.[25] The CCVI incorporates a measure of the percentage of a county's population working in a high-risk industry, and the ADI incorporates occupational composition.

In examining occupational composition along with several other socioeconomic variables that are often included in these indices, this analysis evaluates COVID-19 impact as it is associated with work risk specifically. Understanding which industries have higher outbreak incidence may help better target workplace safety interventions in the future.[5] For example, appropriate sector-specific health education materials can be developed and partnerships between health departments, specific labor unions, and major employers can be nurtured. By better understanding occupational risk during a pandemic and implementing interventions to better protect workers in both times of normalcy and times of emergency, both the healthcare system and overall economy will be better prepared for the growing threat of infectious disease in a globalized world.

2.6 Strengths and Limitations

Because this is an ecologic study, interpretations from this analysis must not infer individual-level risks associated with the variables of interest. This study cannot establish causality between an individual's occupation and their risk of COVID-19 infection, hospitalization, or death. The outcome measures used in the analysis apply to whole communities/geographic areas including but not specific to workers, so as a result, it is difficult to ascertain the direction of the association between occupation and COVID impact at the community level. In exploring how COVID-19 impact changed over time at the community level in relation to the proportion of specific types of essential workers in those communities, however, this study does provide direction and context to future research on COVID-19 risks as they relate to specific occupations. Such research is the focus of Aims 2 and 3 of this dissertation.

Another limitation arises from the fact that testing data for the communities represented in the sample was not publicly available at the same 14-day increments as the case, hospitalization, and death data. Therefore, this study does not incorporate testing access into the monthly and cumulative impact scores. Access to COVID-19 testing varied over time and by community throughout the pandemic, so its exclusion from consideration in these analyses may have affected the results.

It should also be noted that in using the community geographic level, which is analogous to the "Place" geographic level in U.S. Census products, some parts of LA County were not included in the analysis. Using this geographic level was necessary to allow for matching between the ACS data and the LACDPH data, but only 83.6% of the population of the county in 2019 is represented in the sample. Additionally, this "Place" level is comprised of larger areas than other geographic levels such as census tract. This is statistically advantageous but removes some geographic nuance from the analysis.

Finally, this study only examined four of many possible occupational sectors. Selection of the healthcare, first response, education, and food service sectors prioritized essential occupations in which workers were more likely to be working in person and having direct contact with other people at various stages of the pandemic, and was also based on relevance to other parts of this dissertation and availability of existing research. There are many other occupations that required in person work and direct contact with others during the pandemic that should be considered in future research, but were outside the scope of this study.

2.7 References

1. Healthy People 2030: Employment Literature Summary. *U.S. Department of Health and Human Services Office of Disease Prevention and Health Promotion* https://health.gov/healthypeople/priority-areas/social-determinants-health/literature-summaries/employment.

2. Acke, S. *et al.* Global infectious disease risks associated with occupational exposure among non-healthcare workers: a systematic review of the literature. *Occup. Environ. Med.* **79**, 63–71 (2021).

3. Wing, S. *et al.* CHANGING ASSOCIATION BETWEEN COMMUNITY OCCUPATIONAL STRUCTURE AND ISCHAEMIC HEART DISEASE MORTALITY IN THE UNITED STATES. *The Lancet* **330**, 1067–1070 (1987).

4. Armstrong, D., Barnett, E., Casper, M. & Wing, S. Community Occupational Structure, Medical and Economic Resources, and Coronary Mortality among U.S. Blacks and Whites, 1980–1988. *Ann. Epidemiol.* **8**, 184–191 (1998).

5. Heinzerling, A. *et al.* Workplaces Most Affected by COVID-19 Outbreaks in California, January 2020–August 2021. *Am. J. Public Health* **112**, 1180–1190 (2022).

6. Ellingson, K. D. *et al.* Incidence of SARS-CoV-2 Infection Among Health Care Personnel, First Responders, and Other Essential Workers During a Prevaccination COVID-19 Surge in Arizona. *JAMA Health Forum* **2**, e213318 (2021).

7. 2020: American Community Survey 5-Year Estimates. *United States Census Bureau* https://data.census.gov/table?q=healthcare+workers+in+los+angeles+county&t=Industry&y=2020 (2020).

8. Coronavirus in the U.S.: Latest Map and Case Count. *The New York Times* https://www.nytimes.com/interactive/2021/us/covid-cases.html (2020).

9. *American Community Survey and Puerto Rico Community Survey Design and Methodology - Version 3.0*. https://www2.census.gov/programs-surveys/acs/methodology/design_and_methodology/2022/acs_design_methodology_report_2022.pdf (2022).

10. American Community Survey: Sample Size and Data Quality. *United States Census Bureau* https://www.census.gov/acs/www/methodology/sample-size-and-data-quality/.

11. LA County COVID-19 Surveillance Dashboard. *LA County Department of Public Health* http://dashboard.publichealth.lacounty.gov/covid19_surveillance_dashboard/ (2023).

12. Geography Program Glossary. *United States Census Bureau* https://www.census.gov/programs-surveys/geography/about/glossary.html (2022).

13. Walker, K. & Herman, M. tidycensus: Load US Census Boundary and Attribute Data as 'tidyverse' and 'sf'-Ready Data Frames. (2023).

14. Herrero, C. & Villar, A. A synthetic indicator on the impact of COVID-19 on the community's health. *PLOS ONE* **15**, e0238970 (2020).

15. Carrión, D. *et al.* Neighborhood-level disparities and subway utilization during the COVID-19 pandemic in New York City. *Nat. Commun.* **12**, (2021).

16. R Core Team. R: A language and environment for statistical computing. (2023).

17. LAUSD Announces Its Staggered School Reopening Schedule for April. *NBC Los Angeles* https://www.nbclosangeles.com/education/k-12-education/lausd-pandemic-coronavirus-staggered-school-reopening-schedule-april-classrooms-learning-education/2561529/ (2021).

18. Health Equity Tracker. *Health Equity Tracker* https://healthequitytracker.org (2023).

19. Measuring Household Experiences during the Coronavirus Pandemic. *United States Census Bureau* https://www.census.gov/householdpulsedata (2023).

20. Valdez, D., ten Thij, M., Bathina, K., Rutter, L. A. & Bollen, J. Social Media Insights Into US Mental Health During the COVID-19 Pandemic: Longitudinal Analysis of Twitter Data. *J. Med. Internet Res.* **22**, e21418 (2020).

21. CDC. COVID Data Tracker Weekly Review: Interpretive Summary for February 25, 2022. *Centers for Disease Control and Prevention* https://www.cdc.gov/coronavirus/2019-ncov/covid-data/covidview/past-reports/02252022.html (2022).

22. Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L. & Lewis, B. A Social Vulnerability Index for Disaster Management. *J. Homel. Secur. Emerg. Manag.* **8**, (2011).

23. *Vulnerable Communities and COVID-19: The Damage Done, and the Way Forward*. https://surgoventures.org/resource-library/report-vulnerable-communities-and-covid-19 (2021).

24. Singh, G. K. Area Deprivation and Widening Inequalities in US Mortality, 1969–1998. *Am. J. Public Health* **93**, 1137–1143 (2003).

25. Rickless, D., Wendt, M. & Bui, J. Minority Health Social Vulnerability Index Overview.

3 Aim 2: Longitudinal Analysis of Mental Health of Healthcare Workers in Los Angeles, CA During the COVID-19 Pandemic

3.1 Abstract

Background: The COVID-19 pandemic has impacted the mental health of healthcare workers across the U.S. and the world. This study analyzes longitudinal changes in self-reported anxiety symptoms, resilience level, and trauma responses among a cohort of healthcare workers in Los Angeles County between May 2020 and May 2021.

Methods: Logistic mixed effects models were used to explore longitudinal associations between anxiety levels, low resilience, trauma response, and individual risk factors in a cohort of healthcare workers at UCLA Health. Hypothesis tests were used to compare mean anxiety level, resilience level, and trauma response level from throughout the study period across covariate groups.

Results: There were slight positive trends in anxiety and in low resilience level over time in the study cohort. A quadratic time term suggests a slight negative quadratic effect of time may better explain anxiety and resilience levels. The post-vaccine phase of the COVID-19 response was associated with higher odds of anxiety and low resilience compare to the June to mid-December 2020 phase. Younger individuals, females, and those working as nurses had higher odds of anxiety and trauma response compared to older individuals, males, and physicians, respectively. Receiving a vaccine had a protective effect against trauma response (aOR=0.30, 95% CI: 0.12, 0.76) and was associated with lower resilience (aOR=3.28, 95% CI: 1.65, 6.50). Moderate and high hospital occupancy levels were associated with low resilience. Interaction terms suggest the association between bed occupancy and mental health may be moderated by time effects.

Conclusions: There appears to be a trend in mental health outcomes among healthcare workers over the course of the COVID-19 pandemic, possibly related to perceived risk or the stressors and adaptations that occurred during specific phases of the pandemic.

Keywords: COVID-19, anxiety, resilience, trauma, mental health, healthcare workers

3.2 Introduction

As essential workers at the frontlines of response to an epidemic of any infectious disease, healthcare workers are among the most affected groups and are vulnerable to resulting mental health impacts.[1] In addition to being at risk of exposure in their workplace, these workers often must deal with other stressors brought on by the epidemic response, such as limited availability of personal protective equipment, enhanced media attention, and more demanding work hours.[2,3] Previous research from the 2003 SARS and 2014-2015 Ebola epidemics has demonstrated the mental health impacts of infectious disease epidemics on healthcare workers.[4,5]

Since first emerging in the city of Wuhan, China in December 2019, the COVID-19 pandemic has stressed health systems throughout the world.[6] Analyses from throughout the COVID-19 pandemic have confirmed negative impacts on population and health system worker mental health.[7–9] As of December 5, 2022, there have been 5,600,890 hospital admissions of patients with confirmed COVID-19 in the U.S., with the 7-day average peaking at 21,525 in January 2022.[10] In Los Angeles (LA) County, California, hospital admissions of patients with confirmed COVID-19 peaked at 324 per day in January 2021.[11]

Nationally, there were over 15.2 million individuals working in the healthcare or social assistance industries in 2020, which is ~13.8% of the full-time, year-round civilian employed population 16 years and over nationwide.[12] Combined, these two industries employ more than any other industry in the country, including manufacturing, retail trade, and educational services. LA County is the largest county by population in the U.S., with over 10 million residents.[13] In

2020 there were an estimated 442,449 individuals working in the healthcare or social assistance industry in LA County, representing ~13% of the full-time, year-round civilian employed population 16 years and over.[12]

With a large general population and a correspondingly large population of healthcare workers, the impacts of the COVID-19 pandemic on this occupational group in LA quickly became apparent. Between February and May 2020, 9.6% of all reported cases of COVID-19 in LA County occurred in healthcare workers.[14] As of November 11, 2022, there had been 72,268 confirmed COVID-19 infections among healthcare workers and first responders in LA County.[15] However, there remains a dearth of information about the mental health impacts of the pandemic and the pandemic response on these workers in LA County specifically.

Studies of healthcare workers from throughout the pandemic have found high rates of symptoms of anxiety, depression, psychological distress, burnout, and other mental health outcomes.[7,8] Survey data shows there is a gap between the need for mental health care services among healthcare workers and access to those services, but there are limited studies evaluating utilization of mental health care services among healthcare workers.[16]

Many studies have evaluated various mental health outcomes in healthcare workers cross sectionally during the COVID-19 pandemic, but in the context of an extended pandemic that has now lasted for over three years, it is important to understand how these outcomes may change over time on an individual level, how the pandemic response itself has changed over time on a systemic level, and how those systemic changes and other risk factors may be associated with individual outcomes.[17] This study aims to investigate changes in anxiety levels, resilience, trauma response, and mental health care utilization among healthcare workers in LA County throughout the COVID-19 pandemic.

3.3 Methods

3.3.1 Study Design

A cohort study to assess the risk of COVID-19 among healthcare workers in the UCLA Health system enrolled 1,210 healthcare workers beginning in April 2020. Study participants were eligible if they were at least 18 years of age, were employed in a healthcare setting, and were planning to remain at their current workplace for at least the next 6 months at the time of enrollment. Participation was voluntary and recruitment primarily occurred through email engagement with the potential study population and by word-of-mouth.[18]

The study involved collection of biological samples and online survey data twice per month (reduced to once per month in fall 2020) between May 2020 and April 2021, with one final online survey administered in September 2021. Biological samples were used to conduct PCR and serologic testing to identify present and past SARS-CoV-2 infections. Sample collection for PCR testing was performed biweekly and later monthly, while serologic testing was performed monthly. After each study visit, participants received an email with a link to an online questionnaire to complete which included questions on demographic characteristics, potential COVID-19 exposures, vaccine uptake (when that became relevant), mental health, and other risk factors and outcomes. The survey administered in September 2021 included several qualitative questions about mental health care utilization in addition to repeated quantitative questions. While sample collection began in April 2020, survey data collection did not begin until late May 2020, several weeks into the COVID-19 response in California.

In addition to this survey data, the analysis uses longitudinal health system inpatient bed occupancy data from the U.S. Department of Health and Human Services (HHS). The dataset contains facility-level data from all hospitals registered with the Centers for Medicare & Medicaid Services as of June 1, 2020 and aggregates patient impact and hospital bed occupancy data going back to March 2020 on a weekly basis. The dataset was downloaded from the HealthData.gov website.[19]

All survey data from the UCLA Health cohort study was collected and managed in RedCap, hosted by the UCLA Clinical & Translational Science Institute.[20,21]

3.3.2 Ethical Considerations

Ethical approval for this study was obtained from the UCLA Institutional Review Board under IRB #20-000478. Informed consent was obtained from all participants prior to study enrollment.

3.3.3 Measures of Interest

This analysis was conducted to investigate whether anxiety level, resilience, or trauma response is correlated with hospital bed occupancy and other risk factors over time. Anxiety level was measured using the 7-item Generalized Anxiety Disorder (GAD-7) scale, resilience was measured using the Brief Resilience Scale (BRS), and trauma response was measured using the Trauma Screening Questionnaire (TSQ).[22–24] Study participants were asked to complete each of these questionnaires multiple times throughout the study.

The GAD-7 scale consists of 7 questions about problems a respondent may have experienced in the past 2 weeks, with coded answer choices ranging from 0-3. These answers are then summed, providing a total score with a maximum value of 21. Scores of 0-4 may indicate minimal anxiety, scores of 5-9 may indicate mild anxiety, scores of 10-14 may indicate moderate anxiety, and scores of 15+ may indicate severe anxiety. For logistic regression a binary variable was created with a cutoff value of 5 (i.e., <5 and >=5) to capture individuals with minimal to no anxiety and individuals with mild to severe anxiety.

The BRS consists of 6 questions about a respondent's "ability to bounce back and recover from stress," with coded answer choices ranged from 1-5. These answers are then averaged, providing a total score with a maximum of 5, with 1 indicating low resilience and 5 indicating high resilience.[23] For logistic regression, a binary variable was created with the median BRS score from all study observations (3.83) as the cutoff value. A value of "0" was considered to indicate low resilience and a value of "1" was considered to indicate high resilience.

The TSQ typically consists of 10 questions about symptoms of post-traumatic stress disorder (PTSD), or trauma responses, that the respondent may be experiencing. However, because the COVID-19 pandemic was ongoing when the TSQ was administered to study participants, one irrelevant question asking about recurrence of the event was omitted.[ii] This resulted in a maximum possible score of 9 and a minimum possible score of 0. Scores of 6 and higher are considered "positive" for trauma response and risk of PTSD, so a binary variable with a cutoff value of 6 was created to enable logistic regression.[25]

Time, hospital inpatient bed occupancy, and an indicator of individual vaccination status are the main exposures of interest. Time is measured as the number of weeks since study baseline in May 2020 and was scaled to two-week increments to facilitate model interpretation. Time was also examined through the creation of a "pandemic phase" variable with three categories designed to capture different systemic trends during the COVID-19 response. The first category represents the initial phase of the pandemic which included all activities until June 1, 2020, when the County of Los Angeles slowly began to reopen public spaces. The second category represents the sustained response phase between June 1, 2020 and December 14, 2020, and the third represents the post-vaccine phase after vaccines became available to healthcare workers (Figure 3-1). By including both measures of time, we hoped to capture both the effects of the pandemic itself on the mental health of these workers and the effects of the pandemic response in our analysis.

[ii] The omitted question was "Acting or feeling as though the event were happening again."

Initial Phase (beginning of pandemic-May 31, 2020)

- Health authorities are initially notified of the novel virus
- Stay-at-Home order in Los Angeles County
- Healthcare supply shortages
- Many unknowns about disease transmission and severity

Non-pharmaceutical Sustained Response Phase (June 1, 2020-December 13, 2020)

- State of California and Los Angeles County slowly begin to reopen economies
- Health authorities manage response primarily with non-pharmaceutical interventions such as masking, contact tracing, and isolation/quarantine

Vaccination Phase (December 14, 2020-May 31, 2021)

- Multiple vaccines approved for emergency use; distributed to healthcare workers in first eligibility tier
- Vaccine distribution according to tiered eligibility system
- Surge of cases, hospitalizations, and deaths in LA County
- Oxygen shortages at hospitals

Figure 3-1: Pandemic phases used in data analysis

Individual vaccination status is a binary variable that changed from 0 to 1 upon the next follow-up survey after a participant received their first COVID-19 vaccine. Hospital inpatient bed occupancy is calculated for study participants who work in any of the four UCLA hospitals that reported data to HHS: Ronald Reagan Medical Center, Santa Monica Medical Center & Orthopedic Hospital, Los Angeles County/Olive View Medical Center, and Los Angeles County/Harbor Medical Center. Occupancy is measured as the proportion of the average number of occupied staffed inpatient beds over the prior 7-day period to the average number of total staffed inpatient beds over the prior 7-day period, making it a measure of inpatient bed usage over time. In order to better reflect the overall occupancy status of the hospitals, the numerator accounted for all occupied staffed inpatient beds and the denominator accounted for all staffed inpatient beds, not just those beds occupied or designated for COVID-19 patients.

These proportions of inpatient bed usage were then categorized into tertiles to create a categorical variable.

Age at baseline, sex, household income, race, ethnicity, and type of job in healthcare (e.g., doctor/physician, nurse, etc.) are the time-independent covariates included in the models for confounder control and to understand other risk factors associated with anxiety, resilience, and trauma response among healthcare workers throughout the pandemic. Type of job in healthcare was determined by manual categorization of each participant's qualitative response to the question "What is your job title at your primary location of work in the UCLA Health system? (please enter the job title on your employee badge)." If a participant held more than one job role, only their primary job was used in the analysis, so that all job subcategories remained mutually exclusive.

3.3.4 Data Analysis

Descriptive statistics about the study sample were generated, showing frequencies and percentages for categorical variables, or means and standard deviations for continuous variables. Between-group comparisons of mean GAD-7 scores from throughout the entire study used the Kruskal Wallis test.

Exploratory visualizations were also generated, which enabled visual exploration of high-level trends prior to model specification and selection. These visualizations included histograms of all reported GAD-7, BRS, and TSQ scores during the study period from May 2020 through May 2021 (see appendices in Section 3.8) and a series of plots representing the trajectories of the cohort-wide average GAD-7, BRS, and TSQ scores during the study period, as well as the trajectory of hospital inpatient bed occupancy during the study period.

To model change in anxiety levels, resilience, and trauma responses over time during this study in relation to the selected covariates, random intercept and slope mixed effects models were used to account for population-level fixed effects and individual-level random effects. Time, measured as weeks since baseline and scaled to two-week increments, was the random slope.

Linear models of using GAD-7 and TSQ scores as outcome variables showed evidence of non-normality of residuals, so logistic models with binary outcome measured were used instead. The models used a variance components covariance structure and also included interaction terms for categorical hospital bed usage and the two-time variables (linear and quadratic).

Due to a low response rate (n=228) to the ad hoc follow-up survey administered in September 2021, the questions about mental health care utilization are not included in this analysis. Tables showing a high-level analysis of quantitative and qualitative responses to questions about barriers to mental health care access and changes to mental health routines during the COVID-19 pandemic are included in the appendices found in Section 3.7.

Data analysis was primarily conducted using SAS 9.4 (SAS Institute Inc., Cary, NC, USA). Some supplemental analyses were conducted in R.[26]

3.4 Results

A total of 1,158 participants completed at least one survey throughout the study period, although 1,155 completed the baseline survey. However, due to study fatigue, not all study participants regularly completed follow-up surveys, and most had stopped responding by May 2021 (see Table 3-1). To improve precision but maintain enough longitudinal data points, the data used for the analysis was restricted to data collected between May 2020 and May 2021.

The majority of study participants indicated they were female (69.7%), White or Asian (50.7% and 27.0%), and non-Hispanic/Latino (80.5%). The baseline ages of study participants were more evenly distributed, with a median age of 37 (mean age of 39.7). Over two-thirds of participants held clinical jobs such as doctor/physician, nurse, or physician assistant/medical technician/therapist/nurse aid, and 26.0% of participants held administrative jobs such as professor, supervisor, and instructor. Additional demographic characteristics are listed in Table 3-2.

There was a difference in the mean GAD-7 scores from the entire study period among age categories (p<0.001), sex categories (p<0.001), educational levels (p<0.001), race (p=0.024), and job category (p=0.004).

Table 3-1: Number and percent of survey observations, unique respondents, and last follow-ups per month throughout the study (prior to date restriction)

	Observations (n=8954)		**Unique Survey Respondents**		**Last Follow-Ups (n=1149)**	
	n	%	n	%	n	%
May-20	51	0.57	51	4.4	6	0.5
Jun-20	1084	12.11	747	64.5	56	4.8
Jul-20	1373	15.33	711	61.4	24	2.1
Aug-20	1421	15.87	716	61.8	24	2.1
Sep-20	1452	16.22	879	75.9	122	10.5
Oct-20	451	5.04	433	37.4	66	5.7
Nov-20	324	3.62	318	27.5	24	2.1
Dec-20	370	4.13	360	31.1	52	4.5
Jan-21	1026	11.46	678	58.5	227	19.6
Feb-21	290	3.24	266	23.0	50	4.3
Mar-21	210	2.35	185	16.0	12	1.0
Apr-21	283	3.16	255	22.0	67	5.8
May-21	244	2.73	232	20.0	109	9.4
Jun-21	112	1.25	112	9.7	67	5.8
Jul-21	13	0.15	8	0.7	3	0.3
Aug-21	30	0.34	30	2.6	20	1.7
Sep-21	220	2.46	220	19.0	220	19.0

Table 3-2: Baseline demographic characteristics of study participants, May 2020-May 2021 (n=1,157)[a]

	N	%[b]
Study population	1157	100.0
Age at baseline, years (mean: 39.7, std: 10.8)	1099 (5.0% missing)	
18-29	185	16.8
30-39	451	41.0
40-49	249	22.7
50-59	151	13.7
60+	63	5.7
Sex	1131 (2.2% missing)	
Female	788	69.7
Male	343	30.3
Race	1122 (3.0% missing)	
Asian	303	27.0
Black	40	3.6
White	569	50.7
Two or more	60	5.4
Other	118	10.5
Refused	32	2.9
Ethnicity	1078 (6.8% missing)	
Hispanic/Latino	153	14.2
Non-Hispanic/Latino	868	80.5
Prefer not to say	57	5.3
Household income	1128 (2.5% missing)	
$50,000 or less	42	3.7
$50,001-$100,000	292	25.9
$100,001-$150,000	296	26.2
Over $150,000	433	38.4
Don't know/prefer not to say	65	5.8
Education level	1125 (2.8% missing)	
Some college or less	118	10.5
Bachelor's degree	361	32.1
Advanced degree	646	57.4
Primary job	1021 (11.8% missing)	
Doctor/Physician	258	25.3
Nurse	318	31.2
PA, Med Tech, Therapist, Nurse Aid	149	14.6
Admin/Professor, Study Personnel	265	26.0
Other (Laboratory, Pharmacist, Food Service, Janitorial)	31	3.0

[a]Demographic questions were coded as optional for participant comfortability so different variables have different missing rates.

[b]Percentages within each variable are percentages of non-missing responses.

GAD-7 scores from throughout the entire study period were right-skewed, with 1876 (28.1%) individual observations with a GAD-7 score of 0, and a median of 3. However, there were 265 (4.0%) individual observations with scores 15 and higher, which is indicative of severe anxiety, and 540 (8.1%) individual observations with scores between 10-14, which is indicative of moderate anxiety. The highest mean GAD-7 scores from all study participants were reported in

November 2020 (5.0) December 2020 (5.6). The lowest mean GAD-7 scores from all study participants were reported in March and May 2021 (3.8 and 3.6) TSQ scores were also right-skewed, with 3646 (45.8%) individual observations with a score of 0 and a median value of 1. There were 1047 (13.2%) individual observations with scores of 6 or higher, which is indicative of PTSD risk. BRS scores were more evenly distributed, with a median of 3.83 on a 1-5 scale. Figure 3-2, Figure 3-3, and Figure 3-4 show the percentage of GAD-7, BRS, and TSQ scores each month that were categorized as a “1” in the binary version of each variable.

Table 3-3: Comparisons of mean GAD-7 score, mean BRS score, and mean TSQ score over the entire study period by group (n=1,158)[a]

	Mean GAD-7	p-value[a]	Mean BRS	p-value[a]	Mean TSQ	p-value[a]
Study population	4.2		3.7		2.0	
Age at baseline		<0.001		0.002		<0.001
18-29	5.2		3.5		2.3	
30-39	4.5		3.6		2.1	
40-49	4.3		3.6		1.7	
50-59	2.9		3.8		1.5	
60+	2.9		3.7		1.5	
Sex		<0.001		<0.001		<0.001
Female	4.7		3.6		2.2	
Male	3.3		3.8		1.3	
Race		0.56		<0.001		0.024
Asian	4.4		3.5		1.8	
Black	3.3		3.9		1.4	
White	4.3		3.7		2.1	
Two or more	4.3		3.7		2.0	
Other	4.1		3.6		1.6	
Refused	4.6		3.4		2.1	
Ethnicity		0.63		0.16		0.81
Hispanic/Latino	4.6		3.7		2.0	
Non-Hispanic/Latino	4.3		3.6		1.9	
Prefer not to say	5.0		3.5		2.1	
Household income		0.65		<0.001		0.07
$50,000 or less	5.8		3.5		2.3	
$50,001-$100,000	4.3		3.6		2.0	
$100,001-$150,000	4.4		3.6		1.9	
Over $150,000	4.2		3.8		2.0	
Don't know/prefer not to say	3.5		3.6		1.3	
Education level		<0.001		0.05		<0.001
Some college or less	3.5		3.7		1.4	
Bachelor's degree	4.7		3.6		2.1	
Advanced degree	4.2		3.7		1.9	
Primary job		0.003		<0.001		0.004
Doctor/Physician	3.7		3.7		1.8	
Nurse	5.0		3.6		2.3	
PA, Med Tech, Therapist, Nurse Aid	3.9		3.6		1.7	
Admin/Professor, Study Personnel	3.8		3.8		1.8	
Other (Laboratory, Pharmacist, Food Service, Janitorial)	4.2		3.5		1.4	

[a]Kruskal Wallis test

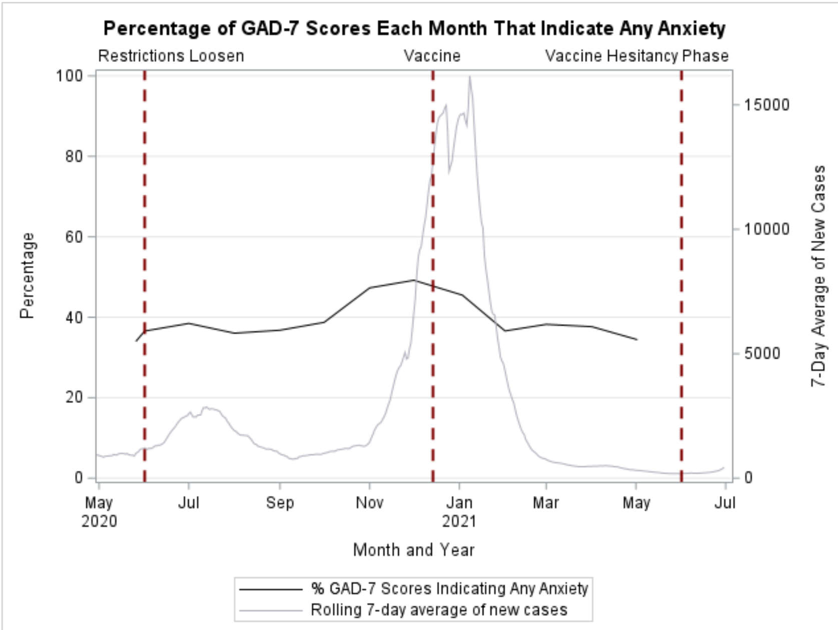

Figure 3-2: Percentage of GAD-7 scores each month that indicate any level of anxiety

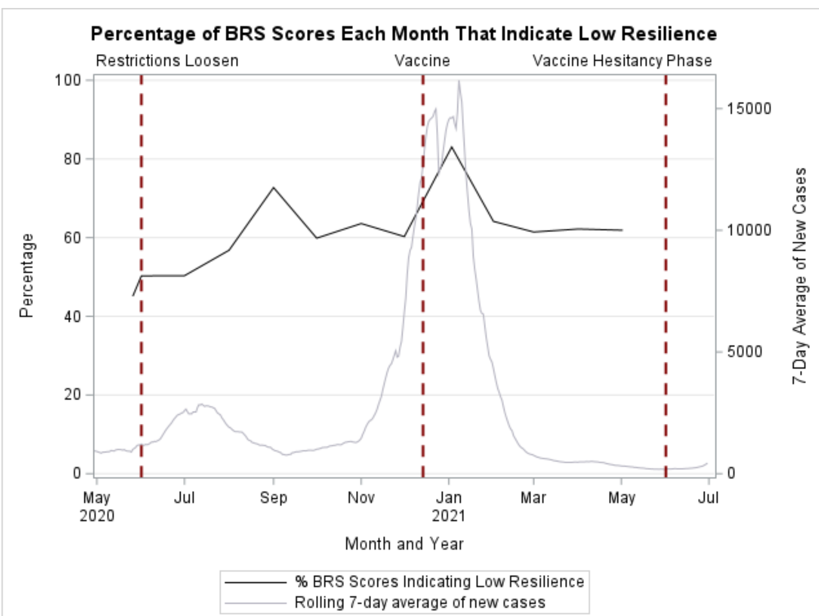

Figure 3-3: Percentage of BRS scores each month that indicate low resilience

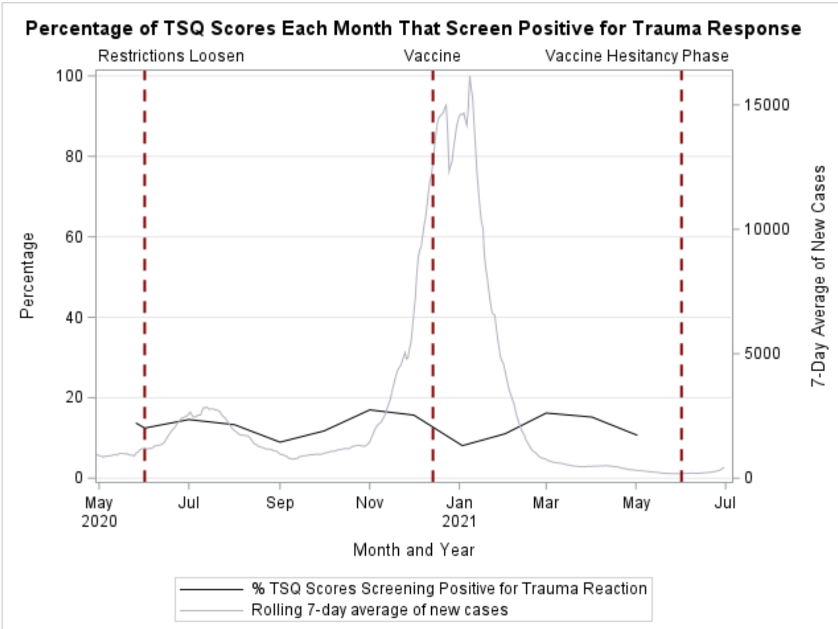

Figure 3-4: Percentage of TSQ scores each month that screen positive for trauma response

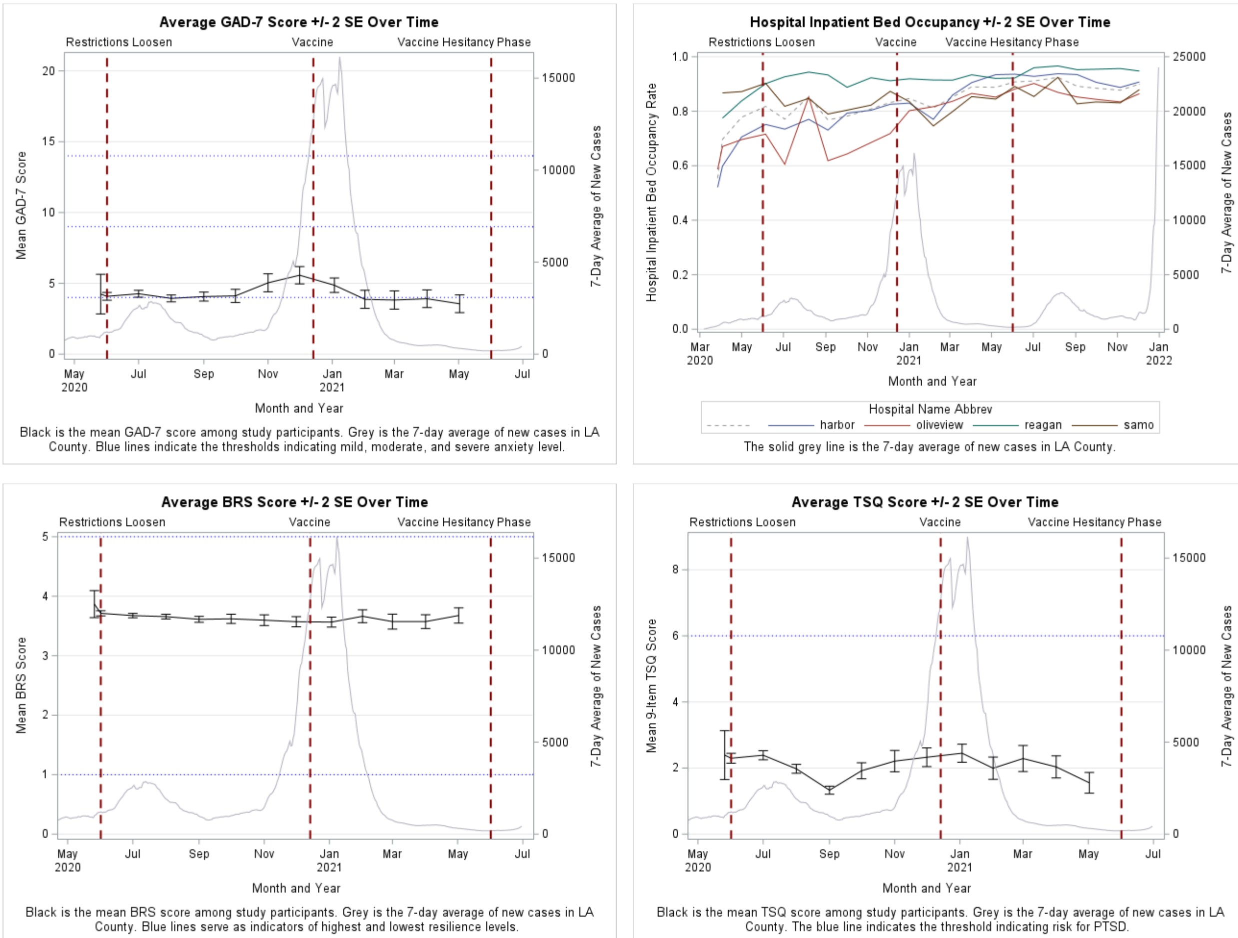

Figure 3-5: Line graphs of mean GAD-7, TSQ, and BRS scores over the study period among all participants, as well as mean hospital capacity over time for each hospital represented as workplaces of study participants

None of the UCLA hospitals examined in this analysis ever exceeded 96.0% inpatient bed occupancy during the study period (May 2020 - May 2021), and the median inpatient bed usage among hospitals represented in the study was 92.6%. Ronald Reagan Medical Center generally had the highest inpatient bed occupancy of the four hospitals between May 2020 and May 2021, and Los Angeles County/Olive View Medical Center generally had the lowest inpatient bed occupancy of the four.

Visual inspection of trends in GAD-7, BRS, and TSQ scores as well as hospital inpatient bed usage over time and in relation to the milestones of initial COVID-19 restrictions loosening, vaccines becoming available, and then vaccine hesitancy emerging as a problem show a slight increase in anxiety and a slight decrease in resilience from the beginning of the study until

December 2020, when vaccines first became available to healthcare workers in California (Figure 3-5).[27] After that, GAD-7 scores begin to decrease and BRS scores begin to increase. TSQ scores decreased in July, August, and September 2020 and then steadily increased until January 2021, when they began to decrease again until summer 2021. Hospital inpatient bed usage steadily increased throughout the study period, with occasional dips in specific hospitals. Results of the three logistic mixed effects models are shown in Table 3-4. Anxiety level and trauma response shared several predictors in their regression models. A one-year increase in age was associated with lower odds of anxiety (aOR=0.92, 95% CI: 0.88, 0.95) and of trauma response (aOR=0.95, 95% CI: 0.91, 0.98). Males had lower odds of anxiety (aOR=0.35, 95% CI: 0.15, 0.84) and of trauma response (aOR=0.25, 95% CI: 0.10, 0.62) compared to females and doctors had lower odds of anxiety (aOR=0.29, 95% CI: 0.11, 0.80) and of trauma response (aOR=0.14, 95% CI: 0.05, 0.39) compared to nurses. Asian individuals had higher odds of low resilience compared to white individuals (aOR=2.01, 95% CI: 1.22, 3.32). Having received a vaccine was associated with lower odds of trauma response (aOR=0.30, 95% CI: 0.12, 0.76) and higher odds of low resilience (aOR=3.28, 95% CI: 1.65, 6.50). The fixed effect of hospital inpatient bed occupancy alone was not associated with anxiety or trauma response, although moderate (aOR=1.66, 95% CI: 1.23, 2.24) and high (aOR=1.59, 95% CI: 1.16, 2.17) levels of hospital inpatient bed occupancy were associated with increased odds of low resilience.
The “Vaccination Phase” of the pandemic response was associated with increased odds of anxiety (aOR=2.82, 95% CI: 1.09, 7.29) and low resilience (aOR=2.68, 95% CI: 1.35, 5.32) compared to the “Sustained Phase.” A two-week increase in time since baseline was associated with an increase in odds of anxiety (aOR=1.21, 95% CI: 1.07, 1.37) and of low resilience (aOR=1.25, 95% CI: 1.14, 1.37). There was an interaction between the linear time variable and hospital inpatient bed usage in the BRS and TSQ models (p-values: 0.002, <0.001, respectively).

The quadratic time variable was associated with slightly lower odds of anxiety (aOR=0.993, 95% CI: 0.988, 0.998) and low resilience (aOR=0.989, 95% CI: 0.985, 0.993), but showed no association with trauma response. There was an interaction between the quadratic time variable and hospital inpatient bed usage in the BRS and TSQ models (p-values: 0.02, 0.002, respectively).

Table 3-4: Associations between GAD-7, BRS, and TSQ scores as binary outcomes and fixed effects

		Any Anxiety[a]		Low Resilience[b]		Trauma Response[c]	
Variables*		aOR[†]	95% CI	aOR[†]	95% CI	aOR[†]	95% CI
Age (continuous)		**0.92**	**(0.88, 0.95)**	1.00	(0.98, 1.02)	**0.95**	**(0.91, 0.98)**
Sex							
	Female	ref	ref	ref	ref	ref	ref
	Male	**0.35**	**(0.15, 0.84)**	0.78	(0.49, 1.25)	**0.25**	**(0.10, 0.62)**
Ethnicity							
	Not Hispanic or Latino	ref	ref	ref	ref	ref	ref
	Hispanic or Latino	1.24	(0.36, 4.24)	0.82	(0.41, 1.62)	0.60	(0.18, 2.04)
	Prefer not to say	1.19	(0.18, 7.81)	1.52	(0.53, 4.36)	0.37	(0.06, 2.52)
Race/Ethnicity							
	White	ref	ref	ref	ref	ref	ref
	Asian	1.77	(0.72, 4.34)	**2.01**	**(1.22, 3.32)**	0.50	(0.20, 1.22)
	Black	4.43	(0.65, 30.33)	0.55	(0.19, 1.63)	0.49	(0.06, 3.98)
	Two or more	1.91	(0.41, 8.96)	0.80	(0.34, 1.89)	0.60	(0.13, 2.86)
	Other	1.38	(0.30, 6.38)	1.47	(0.63, 3.43)	0.97	(0.21, 4.60)
	Refused	1.11	(0.07, 16.56)	1.12	(0.24, 5.35)	2.29	(0.16, 32.00)
Household Income							
	Over $150,000	ref	ref	ref	ref	ref	ref
	$100,001-$150,000	0.42	(0.16, 1.12)	0.99	(0.57, 1.70)	0.65	(0.25, 1.70)
	$50,001-$100,000	**0.33**	**(0.12, 0.89)**	1.02	(0.58, 1.80)	0.58	(0.21, 1.56)
	$50,000 or less	0.17	(0.02, 1.88)	1.36	(0.35, 5.37)	0.18	(0.02, 1.61)
	Don't know/prefer not to say	0.38	(0.07, 2.16)	1.51	(0.57, 3.98)	0.41	(0.07, 2.32)
Primary job							
	Nurse	ref	ref	ref	ref	ref	ref
	Doctor/Physician	**0.29**	**(0.11, 0.80)**	0.70	(0.40, 1.24)	**0.14**	**(0.05, 0.39)**
	PA, Med Tech, Therapist, Nurse Aid	0.44	(0.13, 1.50)	0.93	(0.47, 1.82)	0.39	(0.12, 1.31)
	Admin/Professor, Study Personnel	0.65	(0.22, 1.96)	**0.38**	**(0.21, 0.69)**	0.34	(0.12, 1.01)
	Other	2.04	(0.18, 22.67)	1.19	(0.29, 4.87)	0.49	(0.04, 6.43)
Vaccine Status							
	None	ref	ref	ref	ref	ref	ref
	Any	0.39	(0.15, 1.00)	**3.28**	**(1.65, 6.50)**	**0.30**	**(0.12, 0.76)**
Hospital bed occupancy							
	Low	ref	ref	ref	ref	ref	ref
	Moderate	0.71	(0.47, 1.06)	**1.66**	**(1.23, 2.24)**	0.82	(0.54, 1.27)
	High	0.73	(0.48, 1.11)	**1.59**	**(1.16, 2.17)**	0.79	(0.50, 1.25)
Time Since Study Baseline - linear		**1.21**	**(1.07, 1.37)**	**1.25**	**(1.14, 1.37)**	1.00	(0.87, 1.14)
Time Since Study Baseline - quadratic		**0.993**	**(0.988, 0.998)**	**0.989**	**(0.985, 0.993)**	1.002	(0.997, 1.007)
Pandemic Response Phase							
	Sustained Phase (Jun-mid Dec 2020)	ref	ref	ref	ref	ref	ref
	Initial Phase (Mar-May	0.81	(0.16, 4.11)	0.90	(0.28, 2.88)	2.72	(0.42, 17.50)
	Vaccination Phase (mid Dec 2020-May 2021)	**2.82**	**(1.09, 7.29)**	**2.68**	**(1.35, 5.32)**	0.82	(0.32, 2.12)

an interaction term between time since baseline-squared and hospital capacity

[†]Bolded point estimates are those with p-values < 0.05

[a]Modeling Generalized Anxiety Disorder 7-item scale score as a binary outcome (where a '1' is a GAD-7 score >=5). N=483 (3569 observations)

[b]Modeling Brief Resilience Scale score as a binary outcome (where a '1' is a BRS score >=3.83). N=494 (4660 observations)

3.5 Discussion

This analysis evaluates how individual risk factors, changing hospital bed occupancy, and time, measured continuously and as specific phases of the COVID-19 response, may be associated with mental health outcomes in healthcare workers in LA County from May 2020 through May 2021. Sex and age are well-established as predictors of mental health impacts from the COVID-19 pandemic.[28–30] The impacts of specific systemic factors such as political circumstances, scientific discoveries, and hospital conditions on the mental health and wellbeing of healthcare workers are less thoroughly understood. All of these elements changed throughout the course of the pandemic and it is likely that these changes also affected healthcare worker mental health.

The median hospital bed occupancy among all the hospitals represented as workplaces in the sample was 92.6%, which was very high compared to the rate prior to the pandemic (Table 3-5). While bed occupancy rates were lower at the beginning of the study period, once they increased, they remained high. Staffed hospital bed occupancy rates had been declining in the U.S. from a rate of 76.7 in 1975 to a rate of 65.5 in 2015.31 Inpatient bed utilization rates in LA County and at the four UCLA hospitals included in this study had been increasing slightly since 2012 but were lower than the rates recorded during the COVID-19 pandemic.32 It is notable that this analysis did not detect a straightforward association between hospital inpatient bed occupancy and anxiety or trauma response despite this high occupancy rate compared to the historic trend. Interestingly, moderate and high levels of hospital occupancy were associated with higher odds of low resilience, but were not associated with anxiety or trauma response. Low resilience may act as a proxy for burnout, so the observed association between higher hospital occupancy levels and low resilience may be related to the fact that hospital occupancy increased over time. The interaction the linear time variable and hospital inpatient bed

Table 3-5: Los Angeles County and UCLA hospital bed utilization rates by year (source: California Department of Health Care Access and Information)

	Total Inpatient Bed Utilization (%)	
Year	LA County	4 UCLA Hospitals
2019	59.02	74.58
2018	58.25	73.14
2017	57.13	75.00
2016	57.22	74.89
2015	57.72	74.55
2014	57.09	76.75
2013	56.25	75.82
2012	55.31	69.73

occupancy in the BRS and TSQ models suggest that time-related factors may have an impact on any association between healthcare worker mental health and hospital bed occupancy. While this study did not include a measure of the nurse-to-patient ratio at each hospital, it is important to note that nurse staffing regulations changed in California in December 2020 to allow nurses to care for more patients than what had been the standard.[33] This increase in workload may have had an effect on the mental health of nurses specifically, and may contribute to our findings that nurses had higher odds of anxiety and of trauma response compared to physicians. Additionally, many hospitals in California brought in higher-paid contract nurses to provide surge staffing, which may have impacted staff morale and overall mental health.[34] Future research is needed to understand the impacts of these policies on nurses.

For example, LA County did not experience large-scale hospital capacity challenges at the beginning of the COVID-19 pandemic, as hospitals transitioned to emergency operations and cancelled elective surgeries to create capacity in anticipation of a surge in cases. However, anxiety and trauma response levels among the study population were relatively high at that time. Anxiety and trauma response levels were also high in the November 2020-January 2021 time period, during which time vaccines first became available to healthcare workers but there was a large surge in cases in LA County and a shortage of hospital beds and oxygen supply to treat patients.[35]

It is possible that healthcare worker mental health throughout the pandemic was more significantly impacted by things like supply shortages, testing availability, vaccine availability, community transmission rates, and vaccine hesitancy than hospital bed occupancy itself. Some of these factors are associated with specific phases of the pandemic, and thus may be reflected in the association between the “Vaccination Phase” of the pandemic response and higher odds of anxiety and low resilience compared to the “Non-pharmaceutical Sustained Response Phase”. The dichotomous interpretation of affirmative vaccine status being associated with increased odds of low resilience, but decreased odds of trauma response, may also suggest the influence of shifting systemic trends, such as an increase in available tools to fight the disease along with an increase in vaccine hesitancy and contentious rhetoric in the media.

Finally, the National Academy of Medicine's National Plan for Health Workforce Well-Being, which was released in October 2022 with the goal of strengthening health workforce well-being, calls for statistics on the "use of mental health services and programs."[36,37] The analysis presented here identifies specific sub-populations of healthcare workers that may benefit most from improved engagement and access mental health resources. Future research should evaluate mental health care utilization among healthcare workers throughout the pandemic in order to identify barriers to access and potential areas for targeting policy changes. Such research can highlight gaps that health systems may help address by providing access to mental health care on-site, providing staff resources to find adequate mental health care to meet their needs, and/or giving staff more flexibility to meet their mental health and self-care needs.

It is crucially important that health systems assure their employees that they are supported through all stages of a pandemic response, including before and after, and that they have systems in place to monitor staff wellbeing over time.[2] This study demonstrates the complexity of understanding how many different, and sometimes competing, forces contribute to the overall picture of healthcare worker wellbeing during an extended health emergency response, and additional research will be needed to build out this understanding.

3.6 Strengths and Limitations

This study adds to the dearth of information about how the pandemic and pandemic response affected the mental health of healthcare workers in LA County specifically. It also adds to the growing evidence base of how healthcare workers were impacted longitudinally during the COVID-19 pandemic. The rapid set-up of the study provided COVID-19 testing to healthcare workers at a time in the response when testing opportunities and supplies were difficult to find. It also collected longitudinal data on these workers under real-world conditions throughout an ongoing pandemic response. While this allowed for investigation of how subjects were impacted by the pandemic over time, it also introduced several limitations.

A few limitations of the study must be highlighted. The cohort study used a convenience sample relying heavily upon word-of-mouth for participant recruitment, so it is possible that study participants self-selected if they were more concerned about the pandemic or more vigilant about their health, either of which might be related to mental health, and some level of induced, unmeasured confounding is likely. While there were differences in the average number of survey responses across many covariates, there were not major differences in the average number of survey responses across levels of the three outcome variables, so there is minimal concern about the influence of selection bias. Additionally, all survey data was self-reported, which may have impacted reporting of potentially-sensitive mental health outcomes, although all mental health outcomes were measured using widely validated scales. It should also be noted that the study sample did not capture many individuals with non-clinical or non-academic jobs which, in addition to the racial distribution of the study sample, challenge the generalizability of these findings to healthcare workers more broadly.

There was missing data due to study participants failing to complete all administered surveys on time or at all (Table 3-1). Participants were enabled to skip most questions in the survey to enhance their comfort, but this meant that there are many missing variables even in complete questionnaires. This limited the number of observations that could be used in the regression models. However, data visualizations and hypothesis testing using participants' average GAD-7 scores from throughout the entire study confirm some of the findings of the regression models. Pre-pandemic mental health metrics were not available for the study participants, which made it difficult to assess the true impacts of the pandemic on healthcare worker mental health. While the GAD-7, BRS, and TSQ are well-validated instruments, they only capture pieces of an individual’s overall mental health. Other outcomes of potential interest to better understand the holistic picture of mental include home versus workplace anxiety, stress, and burnout.

3.7 Chapter 3 Appendices

3.7.1 Exploration of loss to follow-up patterns within the study

Table 3-6: Mean and median dropout dates and average number of survey responses by study outcomes and covariates

		Mean Dropout Date	Median Dropout Date	Average # Survey Responses
GAD-7				
	No anxiety	2/23/2021	1/29/2021	7.8
	Any anxiety	3/2/2021	1/31/2021	7.8
BRS				
	Low resilience	2/24/2021	1/29/2021	7.6
	High resilience	2/26/2021	1/29/2021	8.0
TSQ				
	Negative for trauma response	2/23/2021	1/29/2021	7.7
	Positive for trauma response	3/29/2021	4/25/2021	8.2
Age at Baseline				
	18-29	1/17/2021	1/21/2021	6.4
	30-39	2/12/2021	1/26/2021	7.3
	40-49	2/28/2021	1/30/2021	8.2
	50-59	4/7/2021	5/3/2021	9.3
	60+	5/29/2021	6/2/2021	10.5
Sex				
	Female	3/7/2021	2/2/2021	7.9
	Male	1/31/2021	1/24/2021	7.4
Race				
	Asian	2/12/2021	1/26/2021	7.3
	Black	2/25/2021	2/3/2021	8.1
	White	3/10/2021	2/2/2021	8.3
	Two or more	3/1/2021	1/29/2021	6.9
	Other	2/5/2021	1/21/2021	6.7
	Refused	1/16/2021	1/21/2021	6.1
Ethnicity				
	Hispanic/Latino	2/14/2021	1/25/2021	7.1
	Non-Hispanic/Latino	3/2/2021	1/30/2021	8.0
	Prefer not to say	1/6/2021	1/21/2021	6.4
Household Income				
	$50,000 or less	3/11/2021	2/3/2021	6.8
	$50,001-$100,000	2/1/2021	1/25/2021	7.1
	$100,001-$150,000	2/20/2021	1/27/2021	7.6
	Over $150,000	3/14/2021	2/10/2021	8.4
	Don't know/prefer not to say	3/1/2021	2/9/2021	7.6
Education				
	Some college or less	1/18/2021	1/22/2021	7.6
	Bachelor's degree	2/16/2021	1/26/2021	7.0
	Advanced degree	3/9/2021	2/2/2021	8.2
Primary job				
	Doctor/Physician	2/20/2021	1/29/2021	7.6
	Nurse	2/7/2021	1/26/2021	7.6
	PA, Med Tech, Therapist, Nurse Aid	2/9/2021	1/26/2021	7.6
	Admin/Professor, Study Personnel	3/28/2021	4/21/2021	9.3
	Other (Laboratory, Pharmacist, Food Service, Janitorial)	2/15/2021	1/29/2021	7.8

3.7.2 Scatterplot of all reported GAD-7 scores throughout the study

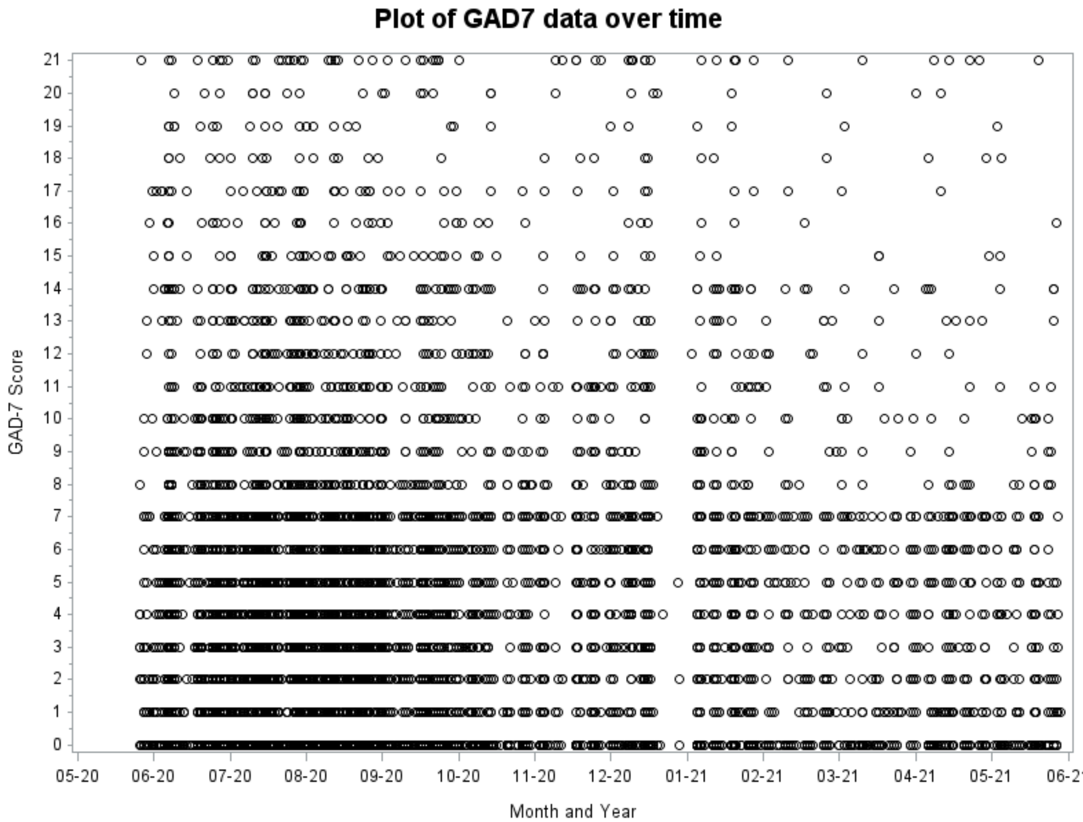

Figure 3-6: Scatterplot of all reported GAD-7 scores throughout the study

3.7.3 Histograms of all reported GAD-7, TSQ, and BRS scores throughout the study

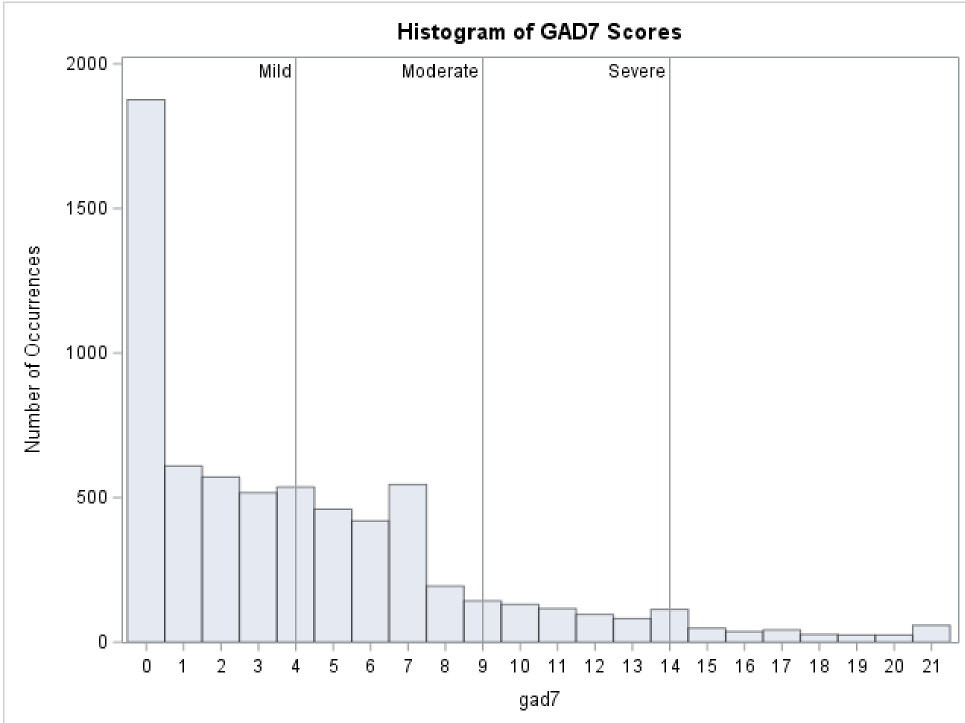

Figure 3-7: Histogram of all reported GAD-7 scores throughout the study

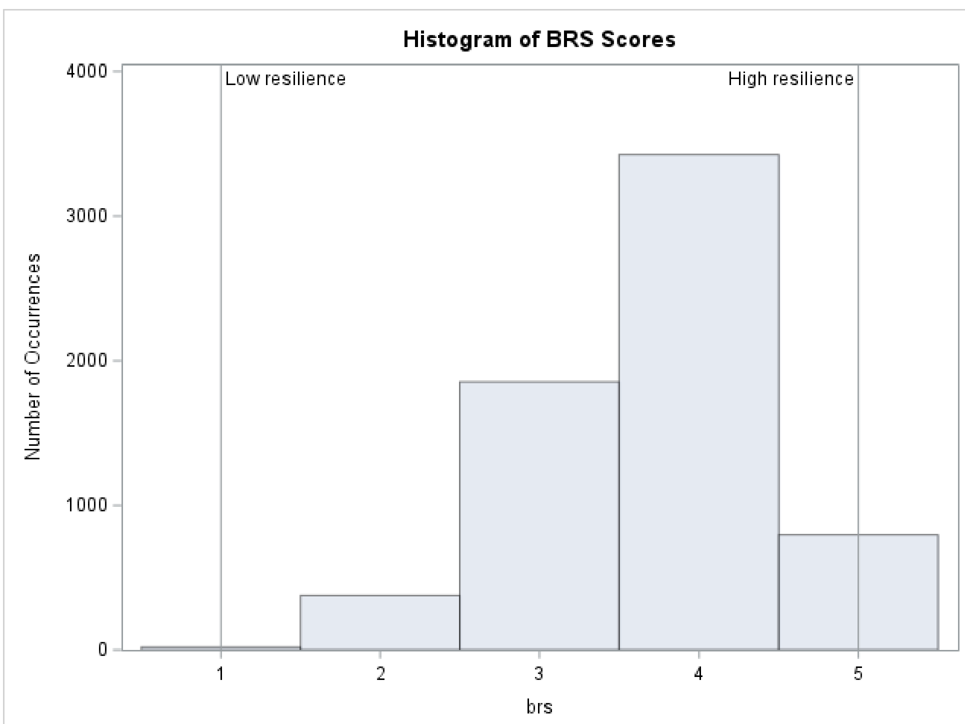

Figure 3-8: Histogram of all reported BRS scores throughout the study

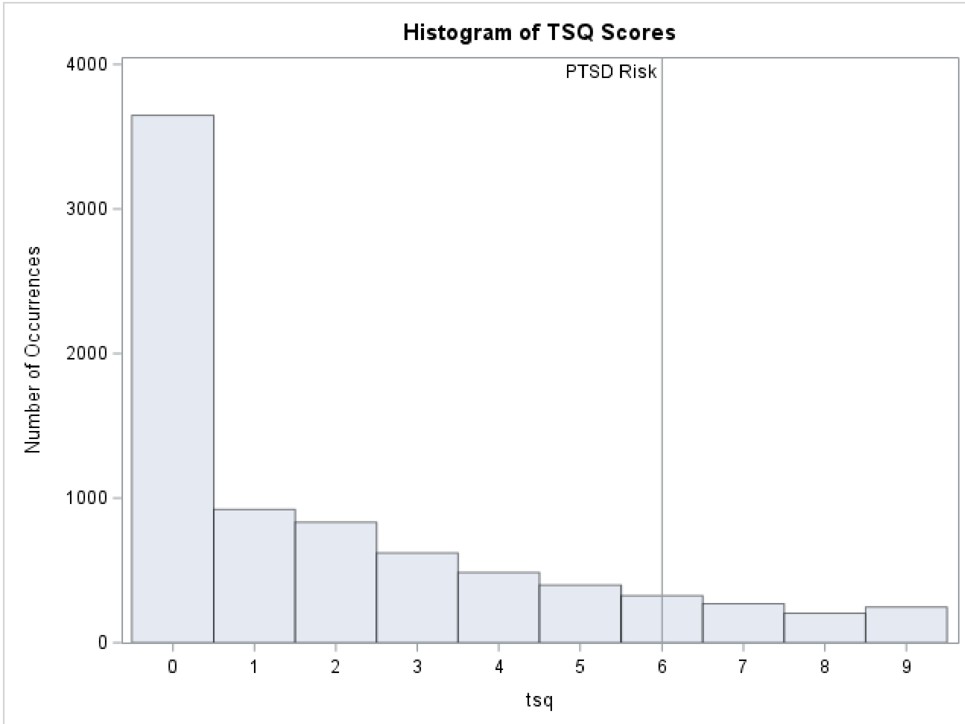

Figure 3-9: Histogram of all reported TSQ scores throughout the study

3.7.4 Line graphs of average GAD-7, BRS, and TSQ scores by job category

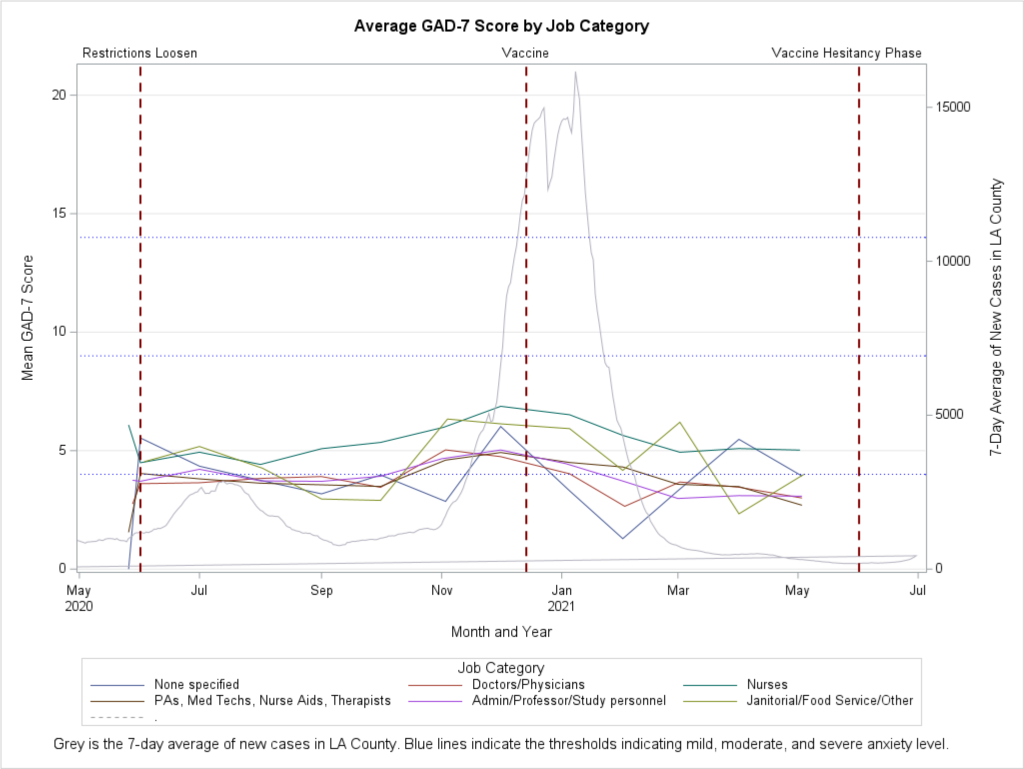

Figure 3-10: Line graph of average GAD-7 score by job category

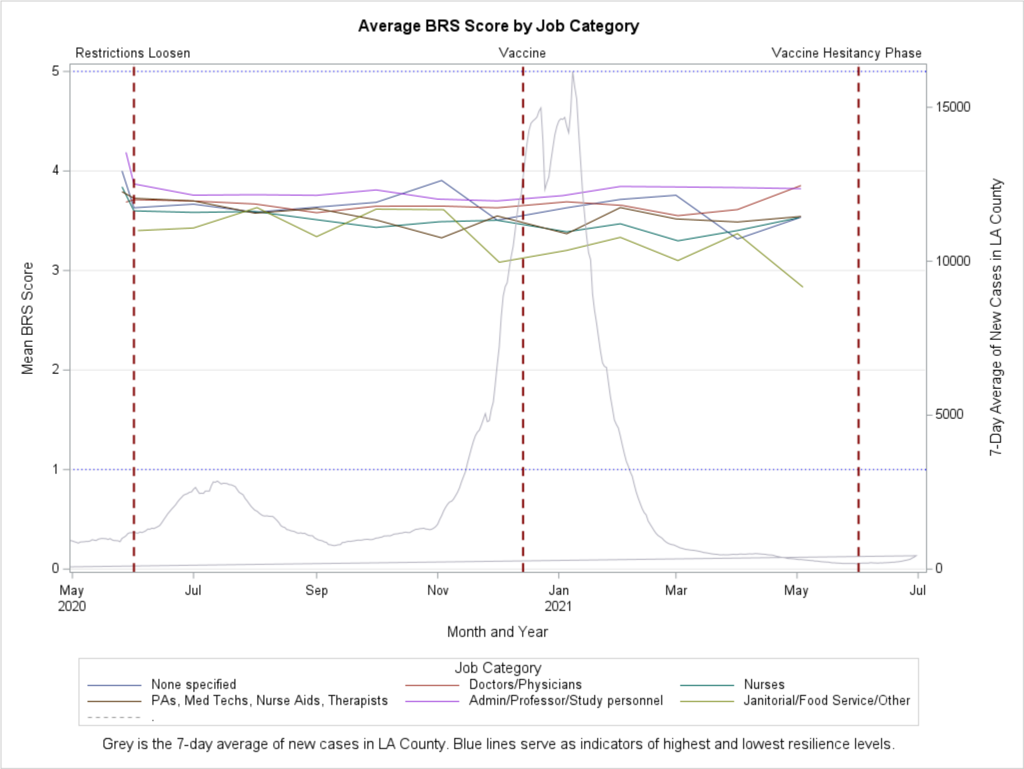

Figure 3-11: Line graph of average BRS score by job category

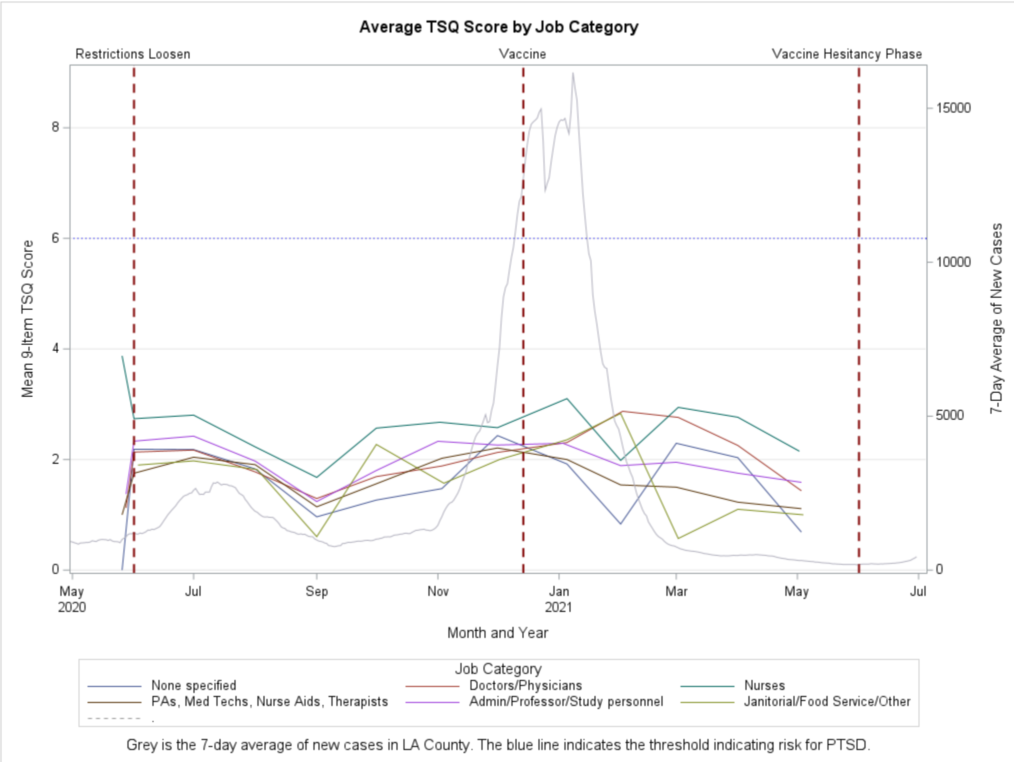

Figure 3-12: Line graph of average TSQ score by job category

3.7.5 Results from September 2021 follow-up survey on mental health care utilization

An additional outcome of interest was participants' utilization of mental health services during the pandemic, and whether or not this use of services changed from before the pandemic. Data on this outcome was collected from a follow-up survey that was administered to the cohort in September 2021 and analyzed in a cross-sectional sub-analysis. Due to a low response rate, the results are included in the appendix.

Due to small cell sizes that failed to meet the assumptions of the chi-square test of independence, the sub-analysis of mental health care utilization within the cohort used Fisher's exact test to test for differences in generalized anxiety levels among those who sought or did not seek mental health services during the pandemic and among those who changed or did not change their mental health care utilization during the pandemic.

Two hundred and twenty-eight study participants completed the follow-up survey administered in September 2021 to assess mental health care utilization among the cohort during the pandemic (Table 3-7). Ages and jobs of respondents were well-distributed, although most respondents (79.6%) were female. 89 respondents (39.0%) of respondents indicated that they sought or wanted to seek care from a mental health professional during the COVID-19 pandemic. Of those 89, 62 (69.7%) reported receiving mental health care. Fifty-nine study participants indicated that their mental health care routine had changed during the pandemic compared to what it had been before. There was a difference in the distribution of GAD-7 score levels among those who sought/didn't seek professional mental health care and those who changed/didn't change their mental health care routine.

The sub-analysis presented here evaluating mental health care utilization in the cohort, while a small sample, is useful for hypothesis generation and for informing how health systems might provide better mental health resources to their personnel. Nearly 40% of respondents had sought or had wanted to seek care from a mental health professional during the pandemic, but only 70% of those who sought that care ultimately received it.

Table 3-7: Demographics and mental health care utilization during the COVID-19 pandemic among a subset of healthcare workers, with test for differences across levels of average GAD-7 score (n=228), Sept 2021

		n	%	p-value*
Age Category		216	100.0%	0.3119
	18-29	22	10.2%	
	30-39	72	33.3%	
	40-49	55	25.5%	
	50-59	41	19.0%	
	60+	26	12.0%	
Gender		221	100.0%	0.3213
	Female	176	79.6%	
	Male	45	20.4%	
Primary job		202	100.0%	0.132
	Doctors/Physicians	49	24.3%	
	Nurses	46	22.8%	
	PAs, Med Techs, Nurse Aids, Therapists	24	11.9%	
	Laboratory, Pharmacists	5	2.5%	
	Admin/Professors, Study Personnel	77	38.1%	
	Janitorial, Food Service, Other	1	0.5%	
Sought or wanted to seek care from a mental health professional during pandemic		228	100.0%	<0.0001
	Yes	89	39.0%	
	No	139	60.1%	
Received care from a mental health professional during pandemic		89	100.0%	0.1923
	Yes	62	69.7%	
	No	27	30.3%	
Mental health care routine changed during pandemic compared to before pandemic		228	100.0%	<0.0001
	Yes	59	25.9%	
	No	169	74.1%	

*Fisher's Exact Test

3.7.5.1 Qualitative Responses to Survey Questions About Mental Health Care

*Table 3-8: Categorized individual responses to survey question: "How did [your mental health routine (e.g., mindfulness, meditation, phone apps)] change [during the COVID-19 pandemic (from March 2020-present) from what it usually was before the pandemic]?"**

Type or Subtype of Self-Care*	# of Responses	Example Quotation
Mindfulness/Meditation/Prayer - General	29	"Have been working more to practice mindfulness."
Mindfulness/meditation apps	10	"Practiced more mindfullness, downloaded a meditiation app"
Journaling	2	"Use of meditation and journaling to help ease anxiety."
Mental Health Interventions - General		
Medication	1	"More focus on controlling anxiety using mindfulness, cognitive behavrioral therapy and medication."
Cognitive Behavioral Therapy	1	*See above*
Coping skills	3	"more in-home self-care (baths, exercise, coping skills)"
Exercise/Physical Activity - General	21	"More regular exercise as a way to manage stress."
Yoga	5	"Started practicing yoga"
Outdoor time	4	"I was more deliberate about making time for exercise and outdoor activities, especially surfing. I used to make plans to surf and then back out, but after COVID, I knew I had to do activities like that to feel calm and whole."
Diet - General	3	"I made more of an effort to engage in routines such as mindfulness mediation, better eating habits and generally allowing myself to have more time to process my feelings"
Diet app	1	"Started exercising and using Noom app"
Vitamins	1	"Took vitamins, regular cardiovascular exercise"
Sleep - General	2	"More attention to sleep and activities that center on me"
Sleep apps	6	"For a time, I used the Calm app for meditation/sleep purposes..."
Self Care - General	10	"Significantly increased the things I did for self-care and adopted new things that helped me adapt and cope with struggles faced during the pandemic."
Breaks at work	1	"More breaks from work, more exercise."
Self-care apps	3	"I utilize self-care apps and talk with more friends and family. I use apps to help with sleep and anxiety."
Hobbies	2	"Actively walking outdoors and doing stairs. Doing hobby: pottery to take my mind elsewhere and make something. Listening to music more"
Personal Relationships - General		
Family/friend time	6	"I spent more time at home with my family"
Social activities	1	"attended more social activities..."
Workplace/coworker support	1	"... more support from co-workers and at work to prevent provider burnout"
Other	4	"Being more mindful of current events and taking necessary precautions"

*68 total participants responded to the survey question, and responses could be coded to multiple types/subtypes of self-care

Table 3-9: Counts and frequencies of responses from participants who indicated they sought or wanted to seek mental health care during the COVID-19 pandemic but never received care as to why they did not receive professional care (n=27)

Why did you not see a mental health professional, despite wanting to seek mental health care?	**n**	**%**
The issue(s) I wanted to discuss got better	2	7.4%
I wanted to handle the issue on my own	5	18.5%
I was unable to find a professional was available at a day/time convenient to me	3	11.1%
I was too busy to find time in my schedule for an appointment	16	59.3%
I did not know how to access mental health care	3	11.1%
I did not feel comfortable seeking mental health care	3	11.1%
I was concerned that someone would find out I was receiving mental health care	1	3.7%
I was concerned that seeking mental health care would negatively impact my career	1	3.7%
The care would have been too expensive	4	14.8%
My health insurance plan does not adequately cover mental health	3	11.1%
My health insurance plan does not cover mental health	2	7.4%
I do not have health insurance	0	0.0%
Other	1	3.7%

3.7.6 Question Scales Used in The Analysis

Table 3-10: The Generalized Anxiety Disorder (GAD-7) scale

Over the <u>last 2 weeks</u>, how often have you been bothered by the following problems?	**Not at all**	**Several days**	**Over half the days**	**Nearly every day**
1. Feeling nervous, anxious, or on edge	0	1	2	3
2. Not being able to stop or control worrying	0	1	2	3
3. Worrying too much about different things	0	1	2	3
4. Trouble relaxing	0	1	2	3
5. Being so restless that it is hard to sit still	0	1	2	3
6. Becoming easily annoyed or irritable	0	1	2	3
7. Feeling afraid, as if something awful might happen	0	1	2	3

Table 3-11: The Trauma Screening Questionnaire (TSQ)

Have you had any of the following outcomes due to the COVID-19 pandemic?	**No**	**Yes**
1. Upsetting thoughts or memories about the pandemic come into your mind against your will	0	1
2. Upsetting dreams	0	1
3. Acting or feeling as though the event were happening again	*Not used in this analysis	
4. Feeling upset about the pandemic	0	1
5. Bodily reactions (such as fast heartbeat, stomach churning, sweatiness, dizziness) when reminded of the event	0	1
6. Difficulty falling or staying asleep	0	1
7. Irritability or outbursts of anger	0	1
8. Difficulty concentrating	0	1
9. Heightened awareness of potential dangers to yourself and others (Have you been more concerned or worried about bad things happening to you or your family?)	0	1
10. Being jumpy or being startled at something unexpected	0	1

Table 3-12: The Brief Resilience Scale (BRS)

Please indicate the extent to which you agree with each of the following statements by using the following scale.	**Strongly Disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
1. I tend to bounce back quickly after hard times.	1	2	3	4	5
2. I have a hard time making it through stressful events.	5	4	3	2	1
3. It does not take me long to recover from a stressful event.	1	2	3	4	5
4. It is hard for me to snap back when something bad happens.	5	4	3	2	1
5. I usually come through difficult times with little trouble.	1	2	3	4	5
6. I tend to take a long time to get over set-backs in my life.	5	4	3	2	1

3.8 References

1. Xiang, Y.-T. *et al.* Timely mental health care for the 2019 novel coronavirus outbreak is urgently needed. *The Lancet Psychiatry* **7**, 228–229 (2020).

2. Shanafelt, T., Ripp, J. & Trockel, M. Understanding and Addressing Sources of Anxiety Among Health Care Professionals During the COVID-19 Pandemic. *JAMA* **323**, 2133–2134 (2020).

3. Newsroom Feature: Health Worker Mental Health. *The National Institute for Occupational Safety and Health (NIOSH)* https://www.cdc.gov/niosh/newsroom/feature/health-worker-mental-health.html (2022).

4. Maunder, R. *et al.* The immediate psychological and occupational impact of the 2003 SARS outbreak in a teaching hospital. *CMAJ* **168**, 1245–1251 (2003).

5. McMahon, S. A. *et al.* Healthcare providers on the frontlines: a qualitative investigation of the social and emotional impact of delivering health services during Sierra Leone’s Ebola epidemic. *Health Policy and Planning* **31**, 1232–1239 (2016).

6. *Impact of the COVID-19 Pandemic on the Hospital and Outpatient Clinician Workforce*. https://aspe.hhs.gov/sites/default/files/documents/9cc72124abd9ea25d58a22c7692dccb6/aspe-covid-workforce-report.pdf (2022).

7. Goodwin Veenema, T. *et al. Mental Health and Social Support for Healthcare and Hospital Workers During the COVID-19 Pandemic*. https://www.centerforhealthsecurity.org/our-work/pubs_archive/pubs-pdfs/2021/20210923-C19-mental-health.pdf (2021).

8. Lai, J. *et al.* Factors Associated With Mental Health Outcomes Among Health Care Workers Exposed to Coronavirus Disease 2019. *JAMA Netw Open* **3**, e203976 (2020).

9. Panchal, N., Saunders, H., Rudowitz, R. & Cox, C. The Implications of COVID-19 for Mental Health and Substance Use. *KFF* https://www.kff.org/coronavirus-covid-19/issue-brief/the-implications-of-covid-19-for-mental-health-and-substance-use/ (2023).

10. COVID Data Tracker. *Centers for Disease Control and Prevention* https://covid.cdc.gov/covid-data-tracker (2023).

11. LA County COVID-19 Surveillance Dashboard. *LA County Department of Public Health* http://dashboard.publichealth.lacounty.gov/covid19_surveillance_dashboard/ (2023).

12. 2020: American Community Survey 5-Year Estimates. *United States Census Bureau* https://data.census.gov/table?q=healthcare+workers+in+los+angeles+county&t=Industry&y=2020 (2020).

13. Largest counties in the U.S. 2020, by population. *Statista* https://www.statista.com/statistics/241702/largest-counties-in-the-us/ (2023).

14. Hartmann, S. *et al.* Coronavirus Disease 2019 (COVID-19) Infections Among Healthcare Workers, Los Angeles County, February–May 2020. *Clinical Infectious Diseases* **73**, e1850–e1854 (2021).

15. *COVID-19 Positive Healthcare Workers and First Responders Data, Los Angeles County*. http://publichealth.lacounty.gov/acd/docs/COVID19HCWReport.pdf (2022).

16. Kirzinger, A., Kearney, A., Hamel, L. & Brodie, M. *KFF/The Washington Post Frontline Health Care Workers*. https://files.kff.org/attachment/Frontline%20Health%20Care%20Workers_Full%20Report_FINAL.pdf (2021).

17. Barzilay, R. *et al.* Resilience, COVID-19-related stress, anxiety and depression during the pandemic in a large population enriched for healthcare providers. *Transl Psychiatry* **10**, 291 (2020).

18. Rimoin, A. W. & Aldrovandi, G. M. Protocol for assessment of potential risk factors for 2019-novel coronavirus (SARS-CoV-2) infection among high-risk populations in health care and emergency service settings. (2021).

19. HHS Office of the Chief Data Officer. COVID-19 Reported Patient Impact and Hospital Capacity by Facility. (2023).

20. Harris, P. A. *et al.* Research electronic data capture (REDCap)—a metadata-driven methodology and workflow process for providing translational research informatics support. *Journal of Biomedical Informatics* **42**, 377–381 (2008).

21. Harris, P. A. *et al.* The REDCap consortium: Building an international community of software partners. *Journal of Biomedical Informatics* **95**, 103208 (2019).

22. Spitzer, R. L., Kroenke, K., Williams, J. B. W. & Löwe, B. A brief measure for assessing generalized anxiety disorder: the GAD-7. *Arch Intern Med* **166**, 1092–1097 (2006).

23. Smith, B. W. *et al.* The brief resilience scale: assessing the ability to bounce back. *International Journal of Behavioral Medicine* **15**, 194–200 (2008).

24. Walters, J. T. R., Bisson, J. I. & Shepherd, J. P. Predicting post-traumatic stress disorder: validation of the Trauma Screening Questionnaire in victims of assault. *Psychological Medicine* **37**, 143–150 (2007).

25. Brewin, C. R. *et al.* Brief screening instrument for post-traumatic stress disorder. *The British Journal of Psychiatry* **181**, 158–162 (2002).

26. R Core Team. R: A language and environment for statistical computing. (2023).

27. Vaziri, A. California's first vaccines administered in L.A., with Newsom looking on. 'This is a day to celebrate'. *San Francisco Chronicle* (2020).

28. Lopes, L., Kearney, A., Kirzinger, A., Hamel, L. & Brodie, M. KFF Health Tracking Poll – December 2020: COVID-19 and Biden's Health Care Agenda. *KFF* https://www.kff.org/coronavirus-covid-19/report/kff-health-tracking-poll-december-2020/ (2020).

29. Santomauro, D. F. *et al.* Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories in 2020 due to the COVID-19 pandemic. *The Lancet* **398**, 1700–1712 (2021).

30. Holingue, C. *et al.* Mental Distress during the COVID-19 Pandemic among US Adults without a Pre-existing Mental Health Condition: Findings from American Trend Panel Survey. *Prev Med* **139**, (2020).

31. *Health, United States, 2017: With Special Feature on Mortality*. https://www.cdc.gov/nchs/data/hus/hus17.pdf (2018).

32. Hospital Annual Utilization Report & Pivot Tables. *California Department of Health Care Access and Information* https://data.chhs.ca.gov/dataset/hospital-annual-utilization-report (2023).

33. Dembosky, A. California Is Overriding Its Limits On Nurse Workloads As COVID-19 Surges. *NPR* (2020).

34. Yang, Y. T. & Mason, D. J. COVID-19's Impact On Nursing Shortages, The Rise Of Travel Nurses, And Price Gouging. *Health Affairs Forefront* (2022) doi:10.1377/forefront.20220125.695159.

35. Tompkins, L., Ives, M. & Shaver, J. W. Running low on oxygen, emergency workers in Los Angeles County are told to administer the minimum necessary. *The New York Times* (2021).

36. Arnold-Forster, A., Moses, J. & Schotland, S. Reading The National Plan For Health Workforce Well-Being Through The Lens Of History. *Health Affairs Forefront* (2022).

37. *National Plan for Health Workforce Well-Being*. https://doi.org/10.17226/26744 (2022).

4 Aim 3: Differences in infection incidence and mental health outcomes between healthcare workers and first responders in Los Angeles County during the COVID-19 pandemic

4.1 Abstract

Background: The COVID-19 pandemic response has placed a high level of stress on healthcare workers and first responders, warranting investigation of the impacts it has had on these occupational groups, both in terms of mental health and overall risk of infection.

Methods: A cohort study enrolled healthcare workers (HCW) and first responders (FR) in Los Angeles County, California to evaluate risk factors for and impacts of COVID-19 infection over time. Logistic regression and chi-square tests were used to compare differences in cumulative infection risk, cumulative vaccination rate, average anxiety level, and average trauma reaction level between HCW and FR. Mixed effects models examined longitudinal associations between various predictors and anxiety level and trauma reaction level.

Results: There were differences by occupational group in infection risk, vaccination rate, anxiety level, and trauma reaction level. Compared to healthcare workers, first responders had a higher cumulative risk of COVID-19 infection, a lower cumulative vaccination rate, and lower levels of both anxiety and trauma reaction. Age, sex, occupational group, and level of perceived professional support were all associated with both mental health outcomes over the study period. First responders had lower odds of anxiety (aOR=0.11, 95% CI: 0.04-0.28) and of trauma reaction (aOR=0.06, 95% CI: 0.01-0.29) than healthcare workers.

Conclusions: Our analysis of a cohort of first responders and healthcare workers in LA County showed differences in COVID-19 infection risk as well as in mental health outcomes by occupational group. Differences in community exposure level, infection prevention practices, and workplace support measures may explain these differences. Therefore, further research on

the effect of specific workplace policies and of individual workers' knowledge, attitudes, and practices on infection risk and mental health outcomes is needed.

Keywords: COVID-19, mental health, anxiety, trauma, healthcare workers, first responders

4.2 Introduction

Healthcare workers and first responders play essential roles in society's response to natural and human-caused disasters.[1] Healthcare workers such as nurses, doctors, and ancillary hospital staff, and first responders such a firefighters, emergency medical technicians, and paramedics were some of the first groups to respond to the arrival of the SARS-CoV-2 virus in the United States.

During the initial phases of the pandemic, the mode of transmission of the virus was not well understood, which, when coupled with a scarcity of personal protective equipment and an increase in the number of COVID-19 patients requiring hospitalization, placed essential workers like healthcare workers and first responders at a higher risk of infection than the general public.[2–4] One study in Arizona found that first responders had a higher risk of SARS-CoV-2 infection than healthcare workers, although few additional studies specifically investigate differences in infection rate between these two groups.[5] Factors that are hypothesized to be associated with this increased risk include frequent contact with the public, fewer implemented infection prevention policies, and a different level of personal mitigation efforts, although these hypotheses require further investigation.[5]

In 2020, there were nearly 66,000 firefighting and prevention and other protective service workers, including supervisors, in Los Angeles (LA) County and over 1.8 million nationally.[6] There were nearly 443,000 individuals working in in the healthcare or social assistance industry in LA County, and over 15.2 million working in that industry nationally.[6] As of November 11, 2022, the LA County Department of Public Health had confirmed COVID-19 infections in 72,268 total healthcare workers and first responders in since the beginning of the pandemic. There had also been 339 confirmed deaths among healthcare workers and first responders in the county as of that time.[7]

The negative impacts of disaster response work on the mental health of first responders as well as healthcare workers has been observed in the context of COVID-19 and in other responses as well.[1,8,9] First responders and healthcare workers have held different roles in the COVID-19 response, and their roles have changed in different ways over time as vaccines have become available and as the disease became better understood. Given this difference in roles, the differential mental health impacts of an extended health emergency response on healthcare workers and on first responders is not well understood.

Some studies have found few to no differences in mental health outcomes between healthcare workers and emergency response personnel such as firefighters, law enforcement officers, and emergency medical services workers.[8,10] Others have found some differences in the prevalence between different job roles within these occupational groups, but few show differences in mental health outcomes between these two occupational groups.[11]

Further investigation of whether there are differences in the impacts the COVID-19 pandemic response has had on healthcare workers and first responders may help identify behavioral, environmental, or workplace policy differences that may be associated with lower infection risk and more positive mental health outcomes during a long-term health emergency response. We therefore conducted a study of healthcare workers and first responders in LA County to assess incidence of COVID-19, level of workplace and community exposures, mental health status, and other outcomes in these workers over time.

4.3 Methods

4.3.1 Study Design

A prospective cohort study to assess risk factors for COVID-19 among healthcare workers (HCW) and first responders (FR) in LA County enrolled healthcare workers from the UCLA

Health System and first responders from the Los Angeles County Fire Department starting in April 2020 and May 2020 respectively. To meet eligibility criteria for participation in the study, subjects had to be at least 18 years of age at the time of enrollment and employed in a healthcare setting or by Los Angeles County in an emergency services/first responder capacity. Subjects also had to be planning to remain employed by their current employer for at least the next six months following enrollment in order to allow for study follow-up. Recruitment for healthcare workers occurred through email engagement and by word-of-mouth. Recruitment for first responders occurred by word-of-mouth and through on-site efforts at fire stations serving as study sites.[12]

We collected biological samples and survey data from participants. Study workers collected biological samples from study participants at repeated study visits over time to test for SARS-CoV-2 and antibodies. After each in-person study visit for sample collection, study participants received a link via email to an online survey to fill out. These online surveys collected data about demographics, clinical history, occupational exposures to COVID-19, community exposures to COVID-19, mental health, and other variables of interest throughout the study period, such as vaccine uptake and attitudes.

Recurring biological sample collection concluded in spring 2021, and online survey data collection concluded in spring 2022. All survey data from both cohorts was collected and managed in RedCap, hosted by the UCLA Clinical & Translational Science Institute.[13,14]

4.3.2 Ethical Considerations

Ethical approval for this study was obtained from the UCLA Institutional Review Board under IRB #20-000478. Informed consent was obtained from all participants prior to study enrollment.

4.3.3 Measures of Interest

The main outcomes of interest examined in this analysis are mental health and COVID-19 infection risk, which was also used as a predictor of interest in some regression models.

Individual infection status is measured by collating several self-reported infection history variables with variables reporting results from COVID-19 tests conducted within and outside of the study. These variables were used to create an indicator variable of whether a study participant had ever been infected with COVID-19, as well as a count variable that increased with each new COVID-19 infection a participant experienced. A new infection was defined as an infection that occurred more than 90 days after the previous infection.[15]

Two scales are used to measure two different mental health outcomes: the 7-item Generalized Anxiety Disorder (GAD-7) scale measures anxiety level and the Trauma Screening Questionnaire (TSQ) measures trauma reaction level to gauge risk of Post-Traumatic Stress Disorder (PTSD).[16,17] The GAD-7 scale is made up of 7 questions about problems the subject may have experienced in the past 2 weeks, each of which has answer choices ranging from "Not at all" (coded as 0) to "Nearly every day" (coded as 3). The coded responses are summed to create a score that can range from 0-21. To account for a high frequency of zeros, this score was converted into a categorical and a binary variable for different elements of the analysis. The categories used for the categorical variable were: minimal anxiety (0-4), mild anxiety (5-9), moderate anxiety (10-14), and severe anxiety (15+). The binary variable used a cutoff score of 5 to indicate subjects with minimal to no anxiety (scores less than 5) and subjects with mild to severe anxiety (scores greater than or equal to 5).

The TSQ consists of 10 symptoms of PTSD to which subjects are asked to indicate whether they have experienced each of those symptoms (yes or no). Due to the ongoing nature of the COVID-19 pandemic at the time this study was conducted, one of those symptoms was removed due to irrelevant phrasing ("Acting or feeling as though the event were happening again"). When all 9 of the included items are summed, there is a minimum possible score of 0 and a maximum possible score of 9. A binary variable was created to indicate risk for PTSD, with a cutoff value of greater than or equal to 6 indicating that a subject may be at risk of experiencing PTSD.

Other predictors of interest included measures of potential COVID-19 exposure risk, vaccination status, and level of perceived professional support. Subjects were asked three questions regarding workplace protection provide by their employer, to which they were asked to respond on a Likert scale ranging from “Strongly Disagree” to “Strongly Agree”. The three questions were: 1) I feel confident in my employer’s ability to protect my wellbeing, 2) I feel that my employer is doing everything in their power to protect me, and 3) I feel that my employer has given me clear instructions/guidelines/policies for worker protection. The answers to these three questions were summed to create a variable gauging a subject’s perceived level of professional support/protection ranging from 3 to 15. This score was also converted to a categorical variable based on tertiles of the distribution of continuous scores to facilitate some analyses. Scores less than 9 corresponded to a perception of a “low” level of professional support, scores from 9-12 corresponded to a “medium” level of perceived professional support, and scores greater than 12 corresponded to a “high” level of perceived professional support.

The regularly-administered online survey also included a series of questions about public areas a subject may have visited in the past 14 days in order to measure a subject’s level of community exposure risk. Subjects were asked to indicate if they had visited any of nine different types of public area (e.g., public transportation, office, etc.) in the past 14 days. All nine of these indicators were then summed to create a continuous variable ranging from 0 to 9. Individual vaccination status was included in the analyses as a binary variable that changed from 0 to 1 once a subject indicated receiving their first dose of COVID-19 vaccine. A binary variable indicating whether a subject had direct patient care and/or civilian contact responsibilities in their role was also examined as a predictor of interest in the analyses.

Age at baseline, sex, race, ethnicity, education level, and occupational cohort (HCW or FR) are the demographic covariates examined in the hypothesis tests and regression models. All these covariates are categorical, with the exception of age, which was continuous.

Time is measured as the number of weeks since study baseline in May 2020 and was scaled to two-week increments to facilitate model interpretation. Time was also examined through the creation of a “pandemic phase” variable with three categories designed to capture different systemic trends during the COVID-19 response. The first category represents the initial phase of the pandemic which included all activities until June 1, 2020, when the County of Los Angeles slowly began to reopen public spaces. The second category represents the sustained response phase between June 1, 2020 and December 14, 2020, and the third represents the post-vaccine phase after vaccines became available to healthcare workers (Figure 4-1).

Initial Phase (beginning of pandemic-May 31, 2020)

- Health authorities are initially notified of the novel virus
- Stay-at-Home order in Los Angeles County
- Healthcare supply shortages
- Many unknowns about disease transmission and severity

Non-Pharmaceutical Sustained Response Phase (June 1, 2020-December 13, 2020)

- State of California and Los Angeles County slowly begin to reopen economies
- Health authorities manage response primarily with non-pharmaceutical interventions such as masking, contact tracing, and isolation/quarantine

Vaccination Phase (December 14, 2020-May 31, 2021)

- Multiple vaccines approved for emergency use
- Vaccine distribution according to tiered eligibility system
- Surge of cases, hospitalizations, and deaths in LA County

Figure 4-1: Pandemic phases used in data analysis

4.3.4 Data Analysis

Descriptive statistics of each cohort, as well as of the entire study population, were generated. These included percentages of categorical variables and means and standard deviations for continuous variables.

Chi-square tests were used to compare cumulative infection rates, cumulative vaccination rates, average anxiety levels, and average trauma reaction level by occupational cohort.

A logistic regression with individual infection status (ever or never infected) as a function of occupational cohort, having public/civilian contact, vaccination status, and average level of perceived professional support in addition to demographic covariates was used to examine risk factors for infection. Accompanying visualizations of new infections and cumulative infection incidence in both cohorts over the course of the study were created to allow for visual examination of change in infection risk over time. Another visualization using a spline regression was generated to allow for further examination of non-linear trends in the data.

Finally, logistic random intercept and slope mixed effects models were used to examine change in anxiety levels and trauma reactions over the study period and in relation to the predictors of interest outlined above. Time, measured in weeks since study baseline and scaled to two-week increments, was the random slope. The models used a variance components covariate structure and included both linear and quadratic terms for time. A set of paired t-tests was used to specifically assess if there was a change in individuals' mean GAD-7 scores before and after vaccines became available in California, and if there was a change in individuals' mean GAD-7 scores before and during the winter 2020-2021 COVID-19 surge in LA County. To complement the paired t-test assessing change in anxiety levels before and after vaccine availability, a difference-in-differences regression was used to evaluate any difference in pre- and post-vaccine availability anxiety level across the two occupational cohorts.

Data analysis and generation of visualizations was conducted in SAS 9.4 (SAS Institute Inc., Cary, NC, USA).

4.4 Results

There were 1,162 total participants in the healthcare worker cohort, of which 1,159 completed a baseline survey. There were 965 total participants in the first responder cohort, of which 923 completed a baseline survey. However, due to study fatigue, not all study participants regularly completed follow-up surveys, and most had stopped responding by May 2021 (see Table 4-1). To improve precision but maintain enough longitudinal data points, the data used for the analysis was restricted to data collected between May 2020 and May 2021, resulting in 2,115 total study participants. Of the 2,115 total study participants, 859 (42.2%) were female and 1175 (57.8%) were male. The first responder cohort had a much higher percentage of male participants (92.1%) than the healthcare worker cohort (30.3%). The first responder cohort had a higher mean age (42.4) and a larger percentage of study participants over the age of 40 (57.8%) compared to the healthcare worker cohort, which had a mean age of 39.7 and 42.1% of participants over the age of 40. There was also a higher percentage of Hispanic or Latino individuals in the first responder cohort (34.4%) compared to the healthcare worker cohort (14.2%). The majority of study participants across both cohorts indicated that their job involves direct contact with patients or with other members of the public. Other demographic statistics may be found in Table 4-2. A chi-square test showed that there was a difference in the percent of individuals indicating they have direct patient or civilian contact in their job by age group ($p<0.001$). The percent of individuals with direct patient or civilian contact decreased as age group increased.

Table 4-1: Number and percent of survey observations, unique respondents, and last follow-ups per month in the study

	Observations (n= 11,804)		**Unique Survey Respondents (n= 2,127)**		**Last Follow-Ups (n= 2,117)**	
	n	%	n	%	n	%
May-20	139	1.18	131	6.16	15	0.71
Jun-20	1330	11.27	960	45.13	101	4.77
Jul-20	1735	14.70	1025	48.19	93	4.39
Aug-20	1854	15.71	1130	53.13	151	7.13
Sep-20	1880	15.93	1246	58.58	257	12.14
Oct-20	658	5.57	630	29.62	159	7.51
Nov-20	397	3.36	375	17.63	31	1.46
Dec-20	605	5.13	489	22.99	99	4.68
Jan-21	1451	12.29	992	46.64	412	19.46
Feb-21	388	3.29	355	16.69	98	4.63
Mar-21	227	1.92	202	9.50	21	0.99
Apr-21	322	2.73	291	13.68	76	3.59
May-21	254	2.15	242	11.38	115	5.43
Jun-21	120	1.02	118	5.55	68	3.21
Jul-21	15	0.13	10	0.47	3	0.14
Aug-21	30	0.25	30	1.41	20	0.94
Sep-21	220	1.86	220	10.34	220	10.39
Oct-21	8	0.07	8	0.38	8	0.38
Nov-21	1	0.01	1	0.05	1	0.05
Dec-21	3	0.03	3	0.14	3	0.14
Jan-22	3	0.03	2	0.09	2	0.09
Feb-22	0	0.00	0	0.00	0	0.00
Mar-22	161	1.36	161	7.57	161	7.61
Apr-22	3	0.03	3	0.14	3	0.14

Table 4-2: Baseline demographic characteristics of study participants by occupational cohort[a]

	All (N=2115)		**Healthcare Workers (N=1158)**		**First Responders (N=957)**	
	N	%	N	%	N	%
Age at baseline, years	2001 (5.4% missing) (mean: 40.9; std: 10.3)		1099 (5.1% missing) (mean: 39.7; std: 10.8)		902 (5.7% missing) (mean: 42.5; std: 9.4)	
18-29	255	12.7	185	16.8	70	7.8
30-39	762	38.1	451	41.0	311	34.5
40-49	494	24.7	249	22.7	245	27.2
50-59	402	20.1	151	13.7	251	27.8
60+	88	4.4	63	5.7	25	2.8
Sex	2034 (3.8% missing)		1131 (2.3% missing)		903 (5.6% missing)	
Female	859	42.2	788	69.7	71	7.9
Male	1175	57.8	343	30.3	832	92.1
Race	2008 (5.1% missing)		1122 (3.1% missing)		886 (7.4% missing)	
Asian	343	17.1	303	27.0	40	4.5
Black	91	4.5	40	3.6	51	5.8
White	1129	56.2	569	50.7	560	63.2
Two or more	102	5.1	60	5.4	42	4.7
Other	255	12.7	118	10.5	137	15.5
Refused	88	4.4	32	2.9	56	6.3
Ethnicity	1916 (9.4% missing)		1078 (6.9% missing)		838 (12.4% missing)	
Hispanic/Latino	441	23.0	153	14.2	288	34.4
Non-Hispanic/Latino	1317	68.7	868	80.5	449	53.6
Prefer not to say	158	8.3	57	5.3	101	12.1
Household income	2021 (4.4% missing)		1128 (2.6% missing)		893 (6.7% missing)	
$50,000 or less	50	2.5	42	3.7	8	0.9
$50,001-$100,000	402	19.9	292	25.9	110	12.3
$100,001-$150,000	532	26.3	296	26.2	236	26.4
Over $150,000	881	43.6	433	38.4	448	50.2
Don't know/prefer not to say	156	7.7	65	5.8	91	10.2
Education level	2015 (4.7% missing)		1125 (2.8% missing)		890 (7.0% missing)	
Some college or less	708	35.1	118	10.5	590	66.3
Bachelor's degree	620	30.8	361	32.1	259	29.1
Advanced degree	687	34.1	646	57.4	41	4.6
Patient or civilian contact	1999 (5.5% missing)		1113 (3.9% missing)		886 (7.4% missing)	
No	299	15.0	128	11.5	171	19.3
Yes	1700	85.0	985	88.5	715	80.7

[a]Demographic questions were coded as optional for participant comfortability so different variables have different missing rates

Comparing cumulative infection rate, cumulative vaccination rate, and levels of general anxiety and trauma reaction by cohort revealed differences in all four outcomes between healthcare workers and first responders (Table 4-3). Of those without missing data for their vaccination status, the HCW cohort had a higher rate of subjects who had received at least one dose of vaccine (94.1%) than did the FR cohort (79.4%). The HCW cohort also had higher percentages of subjects whose average anxiety level throughout the study period were mild, moderate, or severe compared to the FR cohort, and had a higher percentage of individuals whose average trauma reaction level was at or above that indicating PTSD risk. The difference in infection rate between the two cohorts may be seen in Figure 4-2 and Figure 4-3.

Figure 4-2 shows peaks in new infections in healthcare workers in May 2020 and December 2020 and peaks in new infections in first responders in June/July and December 2020. After May 2020, the first responder cohort had a higher cumulative incidence of COVID-19 infections than the healthcare worker cohort throughout the rest of the study. Forty-five participants in the HCW cohort reported ever having been infected with COVID-19 over the study period, and 127 participants in the FR cohort reported ever having been infected during the study period. Only one participant reported having more than one infection over the course of the study period. Cubic splines with 3 knots – at June 2020, September 2020, and December 2021 – fit the data well for both occupational groups and produced an r-square value of 0.988 (Figure 4-4).

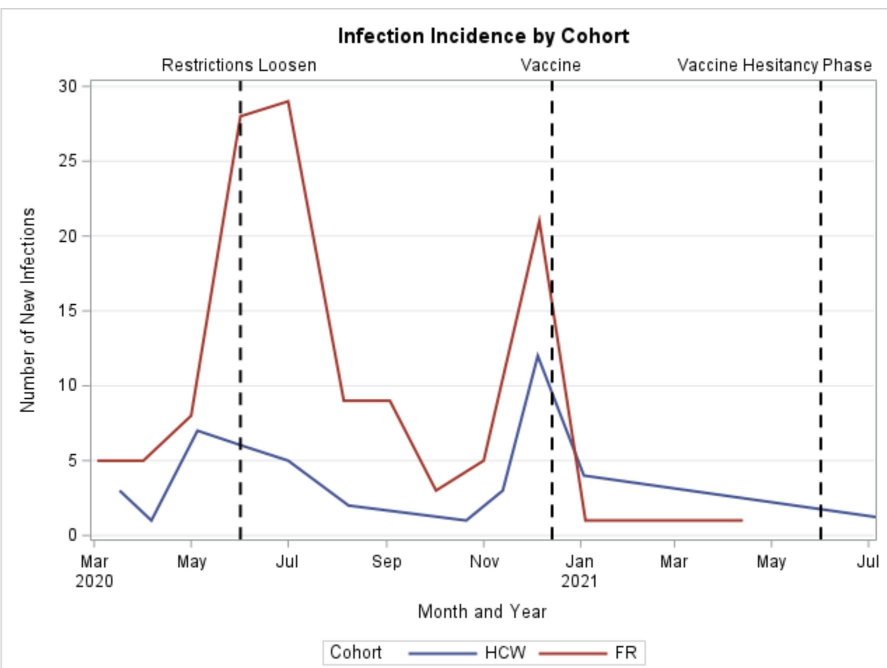

Figure 4-2: Graph of new COVID-19 infections over time by occupational cohort

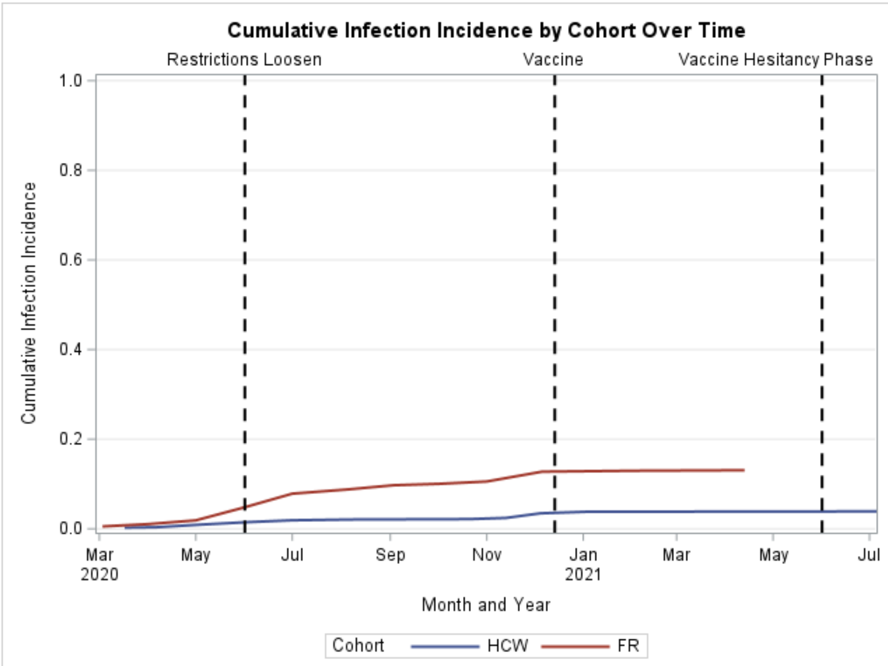

Figure 4-3: Graph of cumulative incidence of COVID-19 over time by occupational cohort

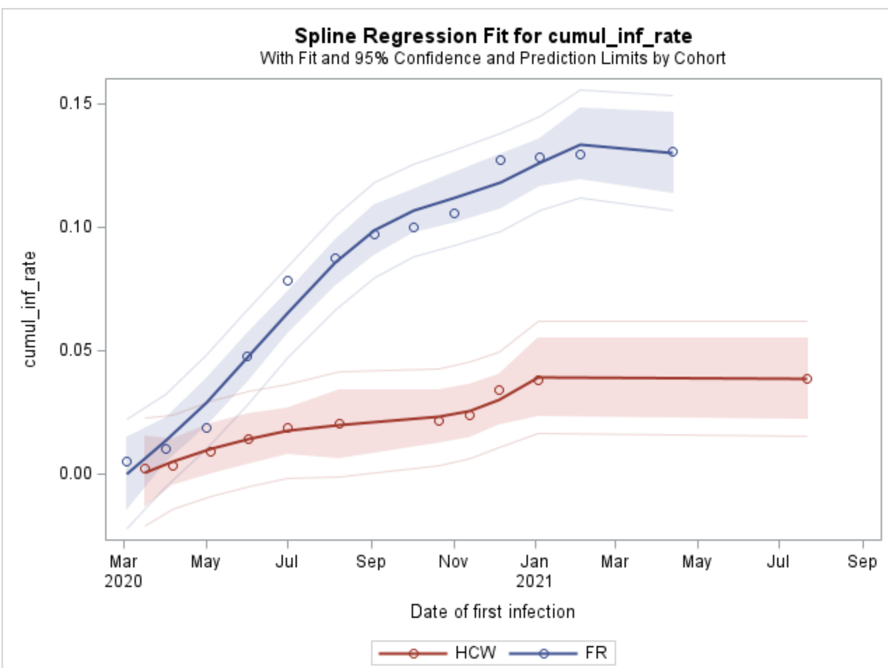

Figure 4-4: Cubic spline regression fit (with 3 knots) for cumulative infection proportion over time in each cohort

Table 4-3: Comparison of cumulative infection rate, cumulative vaccination rate, average anxiety level, and average trauma reaction level by occupational group (May 2020-May 2021)[a]

		Healthcare Workers (N=1158)		First Responders (N=957)		
		N	%	N	%	p-value[b]
COVID-19 infection (ever)		45	3.9%	127	13.3%	<0.001
COVID-19 vaccination (at least 1 dose)[c]		637	94.1%	281	79.4%	<0.001
Average Anxiety Level		1146 (1.0% missing)		930 (2.8% missing)		
	Minimal	727	63.4%	803	86.3%	<0.001
	Mild	296	25.8%	98	10.5%	
	Moderate	89	7.8%	19	2.0%	
	Severe	34	3.0%	10	1.1%	
Average Trauma Reaction		1157 (0.1% missing)		949 (0.8% missing)		
	Below PTSD risk indicator	1079	93.3%	926	97.6%	<0.001
	At or above PTSD risk indicator	78	6.7%	23	2.4%	

[a]Survey questions were coded as optional for participant comfortability and many participants did not complete regular surveys, so different variables have different missing rates
[b]Chi-square test
[c]Denominators are non-missing values for healthcare workers (n=677, 41.5% missing) and first responders (n=354, 63.0% missing)

Table 4-4: Predictors of cumulative infection risk during the study period (May 2020-May 2021)

		Crude		Adjusted*	
Variables		OR	95% CI	OR	95% CI
Occupational group					
	Healthcare Workers	ref	ref	ref	ref
	First Responders	**3.78**	(2.66, 5.38)	**2.52**	(1.12, 5.74)
Patient or Civilian Contact					
	Yes	ref	ref	ref	ref
	No	0.93	(0.58, 1.49)	0.46	(0.20, 1.04)
Vaccination Status					
	Yes (received at least 1 dose)	ref	ref	ref	ref
	No	**1.92**	(1.04, 3.55)	1.42	(0.70, 2.94)
Average Level of Professional Support					
	High	1.34	(0.91, 1.97)	0.72	(0.35, 1.49)
	Medium	ref	ref	ref	ref
	Low	0.91	(0.62, 1.35)	0.76	(0.41, 1.41)
Average Level of Community Exposure					
	Low	ref	ref	ref	ref
	High	1.41	(0.98, 2.03)	0.96	(0.50, 1.82)

*In addition to all listed variables, adjusted model also includes variables for age, sex, ethnicity, race, and education level

Crude models of the associations between occupational group, having patient/civilian contact at work, vaccination status, average level of professional support, and average level of community exposure showed being a first responder is associated with increased odds of infection compared to being a healthcare worker, and that never having been vaccinated is associated with increased odds of infection compared to having received at least one dose of vaccine. First responders still had higher odds of infection after adjusting for occupational cohort, patient or public contact in one’s job, vaccine status, level of professional support, and level of community exposure in additional to demographic covariates, although the estimate attenuated towards the null after adjustment (Table 4-4). Because the cumulative risk of COVID-19 infection was small in both cohorts, we considered the odds ratio to be a reasonable approximation of the risk ratio.

Table 4-5: Fixed effect results from mixed effects models of predictors of anxiety and trauma reaction over the course of the COVID-19 pandemic, May 2020-May 2021

		GAD-7[a]			TSQ[b]	
Variables		aOR*	95% CI		aOR*	95% CI
Age (continuous)		**0.94**	(0.91, 0.96)		**0.93**	(0.89, 0.97)
Sex						
	Male	ref	ref		ref	ref
	Female	**2.98**	(1.51, 5.89)		**8.63**	(3.17, 23.51)
Ethnicity						
	Not Hispanic or Latino	ref	ref		ref	ref
	Hispanic or Latino	1.75	(0.71, 4.28)		1.27	(0.35, 4.59)
	Prefer not to say	1.13	(0.27, 4.74)		0.58	(0.07, 4.95)
Race/Ethnicity						
	White	ref	ref		ref	ref
	Asian	1.38	(0.65, 2.94)		0.47	(0.17, 1.34)
	Black	1.27	(0.28, 5.79)		0.22	(0.02, 2.38)
	Two or more	1.05	(0.28, 4)		0.52	(0.11, 2.56)
	Other	0.91	(0.31, 2.67)		0.17	(0.01, 3.42)
	Refused	1.36	(0.20, 9.38)		0.29	(0.04, 2.05)
Education Level						
	Some college or less	ref	ref		ref	ref
	Bachelor's degree	1.41	(0.53, 3.7)		1.06	(0.23, 4.77)
	Advanced degree	1.54	(0.56, 4.22)		0.81	(0.17, 3.73)
Occupational Group						
	Healthcare Workers	ref	ref		ref	ref
	First Responders	**0.11**	(0.04, 0.28)		**0.06**	(0.01, 0.29)
Patient or Civilian Contact						
	Yes	ref	ref		ref	ref
	No	1.57	(0.70, 3.52)		0.65	(0.20, 2.11)
Vaccination Status						
	No	ref	ref		ref	ref
	Yes (received at least 1 dose)	**0.32**	(0.15, 0.69)		1.76	(0.63, 4.89)
Infection Status						
	Never	ref	ref		ref	ref
	Yes	1.86	(0.62, 5.59)		2.37	(0.46, 12.08)
Professional Support (continuous)		**0.81**	(0.75, 0.86)		**0.81**	(0.73, 0.89)
Community Exposure (continuous)		1.06	(0.95, 1.17)		1.14	(0.99, 1.32)
Time Since Study Baseline - linear		**1.09**	(1.02, 1.17)		**1.20**	(1.09, 1.32)
Time Since Study Baseline - quadratic		**0.997**	(0.994, 1.000)		**0.991**	(0.986, 0.995)
Pandemic Response Phase						
	Sustained Phase (Jun-mid Dec 2020)	ref	ref		ref	ref
	Initial Phase (Mar-May 2020)	0.43	(0.12, 1.52)		2.36	(0.41, 13.54)
	Vaccination Phase (mid Dec 2020-May 2021)	**2.51**	(1.22, 5.16)		1.23	(0.47, 3.24)

[a]Modeling Generalized Anxiety Disorder 7-item scale score as a binary outcome (<5 or >=5). N=860 (5026 observations)
[b]Modeling Trauma Screening Questionnaire score as a binary outcome (<6 or >=6). N=860 (5033 observations)

Results of the two logistic mixed effects models examining longitudinal associations between predictors and the two mental health outcomes of interest are presented in Table 4-5. A one-year increase in age, being a first responder compared to being a healthcare worker, and a higher perceived level of professional support were all associated with lower odds of anxiety and lower odds of a trauma reaction level indicative of PTSD. Having received at least one dose of vaccine was also associated with a decreased odds of anxiety compared with having received no doses of vaccine (aOR=0.32, 95% CI: 0.15, 0.69), but had no association with trauma reaction (aOR=1.76, 95% CI: 0.63, 4.89). Female sex was associated with an increased odds of both anxiety and a higher trauma reaction level compared to male sex.

The linear time term was associated with higher odds of anxiety and higher odds of trauma reaction level indicative of PTSD. The quadratic time variable was associated with a slight decrease in odds in both models, however.

The paired t-test assessing differences in individuals' mean GAD-7 scores after vaccines became available in California, compared to before, failed to reject the null hypothesis of there being no difference in mean GAD-7 scores before and after vaccines became available on December 14, 2020 (p-value: 0.8447).

The paired t-test assessing differences in individuals' mean GAD-7 scores during the winter 2020-2021 surge, compared to before, rejected the null hypothesis of these being no difference in mean GAD-7 scores before and during the surge (p-value<0.001).

Finally, in the difference-in-differences logistic regression model evaluating the difference in post- and pre-vaccine availability anxiety levels by cohort, there was an interaction between cohort and time (p-value<0.001), suggesting that the change in anxiety level after vaccines became available was different for each cohort.

4.5 Discussion

Compared to previous recent pandemics, the COVID-19 pandemic is notable in that healthcare workers, first responders, and public health workers around the world have been responding for over three years. This extended duration of the response not only presented an opportunity for longitudinal examination of infection risk and changes in mental health, it emphasized the importance of understanding factors that impact infection risk and mental health so that interventions may be developed to improve the resiliency of the health workforce for future health emergency responses. Examining differences between the occupational groups that have been most directly involved in the pandemic response can aid in the identification of more effective strategies for infection prevention and mental health protection in the future.

The higher risk of COVID-19 infection in first responders compared to healthcare workers identified in this study is consistent with the findings of another study in Arizona.[5] The findings that females and younger individuals have higher odds of anxiety and trauma are also consistent with existing research.[18,19]

The differences in anxiety levels and trauma reaction levels over time between the two cohorts in this study adds to the limited literature comparing the pandemic effects on these two groups of responders, however, causal explanations of these differences warrant continued investigation. One predictor of interest is level of contact with the public and level of community exposure. Many studies have established the relationship between community contact and risk of COVID-19 infection.[20,21] Due to differences in roles, first responders and healthcare workers have different types of interactions with the community, and different durations of interactions with patients. Better understanding the nature of these patient and community interactions may lead to a better understanding of the transmission risks associated with these interactions and their mental health implications.

Another predictor of interest is that of perceived professional support. It is possible that training frequency or training differences between these two groups leads to a certain level of perceived support which then influences mental health. Differences in training itself may also impact worker resilience, so it is important that emergency response agencies and health systems recognize employee mental health as part of routine emergency preparedness work and prioritize it accordingly in training and exercise planning. Training of managers in strategies such as psychological first aid can aid in implementation of early interventions in future emergency responses.[1] Complementary strategies to prioritize to improve healthcare workforce mental health outcomes include relaxation training, social connectedness, and grief training.

In addition to professional support and training, other workplace policy differences that might explain differences in infection rates or mental health outcomes between these two groups include vaccine mandate timelines, testing mandates and enforcement, and availability of personal protective equipment (PPE). Environmental factors related to the workplace, such as the use of medical-grade HEPA filters in hospitals and implementation of other infection control practices, are another differing factor to consider. Individual behaviors like uptake of vaccines, effective use of PPE, and frequency of community exposure also contribute to overall individual risk of infection and may impact mental health.

Comparing outcomes between occupational groups, as we did in this study, can illuminate how these workplace policy, environmental, and behavioral differences collectively affected worker infection risk and worker mental health during the COVID-19 pandemic. Future research is needed to better understand how specific workplace policies affect these outcomes. It is also important for future research to evaluate the effect of individual worker knowledge, attitudes, and practices on infection risk and mental health. Understanding the complex mechanisms that contribute to these outcomes in the context of a long-term response to a widespread health emergency will not only inform research priorities for rapid response to a future event, but will enable employers and health authorities to implement policies that better protect the health of workers before another health emergency occurs.

4.6 Strengths and Limitations

This study adds to the limited literature comparing the experiences of healthcare workers and first responders during the COVID-19 pandemic. The rapid set-up of the study provided COVID-

19 testing to frontline health workers at a time in the response when testing opportunities and supplies were difficult to find. It also collected longitudinal data on these workers under real-world conditions throughout an ongoing pandemic response. While this allowed for investigation of how subjects were impacted by the pandemic over time, it also introduced several limitations.

One of the limitations of this study is the rate of missing data on many of the predictors and outcomes of interest. Online surveys were designed to allow participants to skip questions to alleviate participant burden, but this increased the rate of missing data. Additionally, because the study followed healthcare workers and first responders in the midst of a pandemic response, many study participants were not able to regularly complete study surveys, leading to longitudinal data that was unbalanced. However, because follow-up surveys repeated many of the same questions over time, there were several opportunities to validate responses on infection and vaccination status, and examination of findings in both longitudinal and cumulative analysis allowed for additional validation of associations.

Another limitation is the reliance on self-reporting for most of the data. It is therefore possible that there is recall bias from study participants misreporting or failing to report their infection history or vaccination history, and it is also possible that there is social desirability bias if participants did not accurately report their mental health status for sensitivity reasons. For example, it is possible that some participants feared negative career repercussions if their survey results screened positive for a mental health disorder.

While the combination of the HCW and FR cohorts generates a study population with demographics that are more balanced than either cohort individually, it is important to note that the study population still may not be generalizable to frontline workers in other sectors or in other regions that have different demographic makeups.

Aside from the survey questions about the public areas a subject had visited in the past 14 days, the study did not include additional repeated measures to gauge a subject's level of risk of invoicommunity transmission of the SARS-CoV-2 virus. Inclusion of a more robust set of measures on community exposure risk would have enhanced improved the analytic capability to evaluate the contribution of community exposures versus workplace exposures to overall infection risk.

Additionally, the study did not discretely measure level of home-life support or level of home-life related stress. Without such measures, it is difficult to disentangle the contributions of and interactions between professional support, professional stress, home-life support, and home-life stress in affecting individual mental health outcomes.

4.7 Chapter 4 Appendices

4.7.1 Exploration of loss to follow-up patterns in the study

Table 4-6: Mean and median dropout dates and average number of survey responses by study outcomes and covariates

		Mean Dropout Date	Median Dropout Date	Average # Survey Responses
GAD-7				
	No anxiety	2/7/2021	1/21/2021	5.4
	Any anxiety	2/24/2021	1/25/2021	6.6
TSQ				
	Negative for trauma reaction	2/8/2021	1/21/2021	5.6
	Positive for trauma reaction	3/15/2021	2/10/2021	7.0
Age at Baseline				
	18-29	1/9/2021	12/14/2020	5.4
	30-39	1/22/2021	1/21/2021	5.4
	40-49	2/14/2021	1/21/2021	5.5
	50-59	3/14/2021	1/25/2021	5.6
	60+	5/19/2021	5/24/2021	8.5
Sex				
	Female	3/14/2021	2/2/2021	7.6
	Male	1/18/2021	12/15/2020	4.1
Race				
	Asian	2/13/2021	1/25/2021	7.0
	Black	2/6/2021	1/25/2021	5.5
	White	2/21/2021	1/22/2021	5.6
	Two or more	2/14/2021	1/21/2021	5.2
	Other	1/17/2021	1/6/2021	4.7
	Refused	11/27/2020	9/30/2020	3.6
Ethnicity				
	Hispanic/Latino	1/25/2021	1/7/2021	4.3
	Non-Hispanic/Latino	2/25/2021	1/25/2021	6.3
	Prefer not to say	12/20/2020	11/30/2020	4.0
Household Income				
	$50,000 or less	3/4/2021	1/29/2021	5.9
	$50,001-$100,000	1/28/2021	1/21/2021	5.9
	$100,001-$150,000	1/24/2021	1/21/2021	5.4
	Over $150,000	2/25/2021	1/23/2021	5.7
	Don't know/prefer not to say	2/12/2021	1/21/2021	5.1
Education				
	Some college or less	1/6/2021	11/6/2020	3.5
	Bachelor's degree	2/14/2021	1/21/2021	5.4
	Advanced degree	3/17/2021	2/4/2021	7.9
Occupational Group				
	HCW	2/28/2021	1/29/2021	7.9
	FR	1/29/2021	11/20/2020	2.8

4.8 References

1. Benedek, D. M., Fullerton, C. & Ursano, R. J. First Responders: Mental Health Consequences of Natural and Human-Made Disasters for Public Health and Public Safety Workers. *Annu. Rev. Public Health* **28**, 55–68 (2007).

2. McGuire, S. S., Klassen, A. B., Heywood, J. & Sztajnkrycer, M. D. Prevalence of COVID-19 IgG Antibodies in a Cohort of Municipal First Responders. *Prehospital Disaster Med.* **36**, 131–134 (2021).

3. Goodwin Veenema, T. *et al. Mental Health and Social Support for Healthcare and Hospital Workers During the COVID-19 Pandemic*. https://www.centerforhealthsecurity.org/our-work/pubs_archive/pubs-pdfs/2021/20210923-C19-mental-health.pdf (2021).

4. Weiden, M. D. *et al.* Pre-COVID-19 lung function and other risk factors for severe COVID-19 in first responders. *ERJ Open Res.* **7**, 00610–02020 (2021).

5. Ellingson, K. D. *et al.* Incidence of SARS-CoV-2 Infection Among Health Care Personnel, First Responders, and Other Essential Workers During a Prevaccination COVID-19 Surge in Arizona. *JAMA Health Forum* **2**, e213318 (2021).

6. 2020: American Community Survey 5-Year Estimates. *United States Census Bureau* https://data.census.gov/table?q=healthcare+workers+in+los+angeles+county&t=Industry&y=2020 (2020).

7. *COVID-19 Positive Healthcare Workers and First Responders Data, Los Angeles County*. http://publichealth.lacounty.gov/acd/docs/COVID19HCWReport.pdf (2022).

8. Hendrickson, R. C. *et al.* The Impact of the COVID-19 Pandemic on Mental Health, Occupational Functioning, and Professional Retention Among Health Care Workers and First Responders. *J. Gen. Intern. Med.* **37**, 397–408 (2022).

9. Maunder, R. *et al.* The immediate psychological and occupational impact of the 2003 SARS outbreak in a teaching hospital. *CMAJ Can. Med. Assoc. J.* **168**, 1245–1251 (2003).

10. Wright, H. M. *et al.* Pandemic-related mental health risk among front line personnel. *J. Psychiatr. Res.* **137**, 673–680 (2021).

11. Lai, J. *et al.* Factors Associated With Mental Health Outcomes Among Health Care Workers Exposed to Coronavirus Disease 2019. *JAMA Netw. Open* **3**, e203976 (2020).

12. Rimoin, A. W. & Aldrovandi, G. M. Protocol for assessment of potential risk factors for 2019-novel coronavirus (SARS-CoV-2) infection among high-risk populations in health care and emergency service settings. (2021).

13. Harris, P. A. *et al.* Research electronic data capture (REDCap)—a metadata-driven methodology and workflow process for providing translational research informatics support. *J. Biomed. Inform.* **42**, 377–381 (2008).

14. Harris, P. A. *et al.* The REDCap consortium: Building an international community of software partners. *J. Biomed. Inform.* **95**, 103208 (2019).

15. Coronavirus Disease 2019 (COVID-19) 2021 Case Definition. *Centers for Disease Control and Prevention* https://ndc.services.cdc.gov/case-definitions/coronavirus-disease-2019-2021/ (2021).

16. Spitzer, R. L., Kroenke, K., Williams, J. B. W. & Löwe, B. A brief measure for assessing generalized anxiety disorder: the GAD-7. *Arch. Intern. Med.* **166**, 1092–1097 (2006).

17. Walters, J. T. R., Bisson, J. I. & Shepherd, J. P. Predicting post-traumatic stress disorder: validation of the Trauma Screening Questionnaire in victims of assault. *Psychol. Med.* **37**, 143–150 (2007).

18. Santomauro, D. F. *et al.* Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories in 2020 due to the COVID-19 pandemic. *The Lancet* **398**, 1700–1712 (2021).

19. Holingue, C. *et al.* Mental Distress during the COVID-19 Pandemic among US Adults without a Pre-existing Mental Health Condition: Findings from American Trend Panel Survey. *Prev. Med.* **139**, (2020).

20. Jacob, J. T. *et al.* Risk Factors Associated With SARS-CoV-2 Seropositivity Among US Health Care Personnel. *JAMA Netw. Open* **4**, e211283 (2021).

21. Johansson, M. A. *et al.* SARS-CoV-2 Transmission From People Without COVID-19 Symptoms. *JAMA Netw. Open* **4**, e2035057 (2021).

5 Conclusion

5.1 Concluding Remarks

The impacts that the COVID-19 pandemic have had on the physical and mental health of essential workers in the United States over the past three years are the product of individual, familial, community-based, occupational, governmental, and other factors.

Individuals who work in certain occupations (e.g., healthcare) are at higher risk of COVID-19 infection at work than individuals who work in other industries that allow for remote work.[1] However, "less is known about infection risk for first responders and other essential workers than for healthcare personnel," and few studies have been conducted that compare risk across different occupational groups in the U.S.[2] There are even fewer that compare risk across occupational groups in Los Angeles County.

With this dissertation I hope to add nuance to the understanding of how the pandemic has impacted these workers, particularly their mental health. I also hope to demonstrate the utility of incorporating multiple publicly available datasets into investigations of an ongoing infectious disease pandemic to expand the possible analytical options.

5.2 Future Research

While this research specifically examined the role of workplace factors in mental health, individuals experience many other sources of both stress and support throughout their daily lives. Future research is needed to distinguish contributions of workplace support and stressors from home and community-based support and stressors to a worker's overall mental health.

A study evaluating the occurrence of long-term health problems in healthcare workers post-COVID-19 found that they were reluctant to seek medical advice or take additional sick leave.[3] Such reluctance may further contribute to burnout and declining mental health, and so it is important for future studies to further examine why these workers are hesitant to seek medical advice. As Chapter 3 demonstrates, qualitative methods may be useful in understanding such decisions.

Qualitative or mixed methods may also be useful in identifying opportunities for employers to provide improved tools and training to their employees. The implementation of different occupational exposure control measures may explain some of the variation in risk across occupations identified in Chapter 4, and mixed methods may allow for identification of these differences. Mixed methods can also help identify training gaps that employers can address. Some research from throughout the COVID-19 pandemic examined how different coping mechanisms and stress reduction techniques may help manage mental health. Listening to music was associated with lower levels of stress and improved mood, and many mindfulness “micropractices” can have significant positive impacts on mental wellbeing.[4,5] Pilot studies should be organized to understand the feasibility and effectiveness of implementing some of these strategies in the workplace.

5.3 Public Health Importance / Policy Implications

The COVID-19 pandemic has placed enormous pressure on essential workers across the economy. In areas heavily affected by COVID-19, health system workers and first responders have been faced with increased workload, lack of personal protective equipment, increased media attention, and poorly prepared health systems. Education workers have been impacted by repeated shifts between remote and in-person work while trying to keep students engaged, outdated ventilation systems, and contentious public debate about when and how to reopen schools. Many food service workers have dealt with temporary unemployment, unenforced public health orders, and challenging customers throughout the last three years.

All of the above stressors may contribute to burnout, leading to many workers in these essential sectors leaving their jobs. Additionally, long COVID is causing some affected workers to reduce their work hours or leave the workforce entirely while they deal with the long-term effects of their illness.[6] As a result of all of these forces, there are current workforce shortages in health care, teaching, food service, and in the general U.S. economy.[7–9]

The politization of the COVID-19 response and diverging societal attitudes towards healthcare and public health guidelines have also affected the mental health of workers. In particular, healthcare workers around the world experienced stigma, discrimination, threats, harassment, and physical violence from patients and the general public. Some of these actions were motivated by fear of disease transmission, while others were motivated by anger over public health rules or mistrust of the health system. Experiencing such treatment is associated with increases in symptoms of many mental health disorders.[10,11] Public health workers and school personnel experienced similar treatment throughout the pandemic as well.[12,13] Governments around the world can do more to provide safer working environments for all types of workers and to ensure workers receive the mental health support they need.[14]

The most recent Mental Health Atlas from the WHO showed that governments around the world spend a median of 2.1% of their total health expenditures on mental health.[15] In 2016, 6% of U.S. health care spending went to behavioral health.[16] This highlights an opportunity for the federal, state, and local government to dedicate more resources to mental and behavioral health so that the mental health care system is better equipped to deal with future surges in demand for any reason. Some studies have found an association between pandemic policy stringency and poorer mental health.[17] This highlights the importance of establishing effective systems of care before they are needed during an emergency response, which mitigates the need to establish such stringent policies during a response. Additionally, there is an opportunity for employers to better serve the physical and mental health needs of their employees by establishing improved policies and tools for future health emergencies. It will be important for employers to work with researchers to validate and deploy screening tools that are specifically tailored to the workplace stressors faced by health first responders during both acute and prolonged health emergencies. One such example is the Stress and Anxiety to Viral Epidemics-9 (SAVE-9) scale.[18]

On July 16, 2021, the U.S. Department of Health and Human Services (HHS) announced specific funding through the American Rescue Plan to be used towards reducing burnout and promoting mental health among the health workforce.[19] Additionally, the CDC's COVID-19 Information Metrics for Response Leadership's Decision Making recommends "number and proportion of responders reporting mental health symptoms, psychological stressors, and poor resilience" as a metric to inform COVID-19 response decisions.[20]

The provision of this funding and recognition of mental health outcomes in decision making are crucial steps in establishing a culture of wellness in the health and public safety workforce. It will be critical that ongoing efforts in this area specifically recognize the needs of health workers in rural and medically underserved areas as well.

It is critically important to expand similar funding initiatives to support workers in other essential sectors as well, as many workers outside of health care and emergency response were adversely impacted, both physically and mentally, by the pandemic response. Efforts to bolster worker wellness and to improve preparedness across sectors of the economy will mitigate the worst impacts of future health emergencies.

5.4 References

1. Mutambudzi, M. *et al.* Occupation and risk of severe COVID-19: prospective cohort study of 120 075 UK Biobank participants. *Occup. Environ. Med.* **78**, 307–314 (2021).

2. Ellingson, K. D. *et al.* Incidence of SARS-CoV-2 Infection Among Health Care Personnel, First Responders, and Other Essential Workers During a Prevaccination COVID-19 Surge in Arizona. *JAMA Health Forum* **2**, e213318 (2021).

3. Gaber, T. A.-Z. K., Ashish, A. & Unsworth, A. Persistent post-covid symptoms in healthcare workers. *Occup. Med. Oxf. Engl.* **71**, 144–146 (2021).

4. Feneberg, A. C. *et al.* Perceptions of Stress and Mood Associated With Listening to Music in Daily Life During the COVID-19 Lockdown. *JAMA Netw. Open* **6**, e2250382 (2023).

5. Fessell, D. & Cherniss, C. Coronavirus Disease 2019 (COVID-19) and Beyond: Micropractices for Burnout Prevention and Emotional Wellness. *J. Am. Coll. Radiol.* **17**, 746–748 (2020).

6. Bach, K. *Is 'long Covid' worsening the labor shortage?* https://www.brookings.edu/research/is-long-covid-worsening-the-labor-shortage/ (2022).

7. Fact Sheet: Strengthening the Health Care Workforce. (2021).

8. Schmitt, J. & deCourcy, K. *The pandemic has exacerbated a long-standing national shortage of teachers*. https://www.epi.org/publication/shortage-of-teachers/ (2022).

9. Ferguson, S. Understanding America's Labor Shortage: The Most Impacted Industries. *U.S. Chamber of Commerce* https://www.uschamber.com/workforce/understanding-americas-labor-shortage-the-most-impacted-industries (2023).

10. Tiesman, H. M. *et al.* Workplace Violence and the Mental Health of Public Health Workers During COVID-19. *Am. J. Prev. Med.* **64**, 315–325 (2023).

11. Havaei, F. Does the Type of Exposure to Workplace Violence Matter to Nurses' Mental Health? *Healthc. Basel* **9**, 41 (2021).

12. Yeager, V. A. The Politicization of Public Health and the Impact on Health Officials and the Workforce: Charting a Path Forward. *Am. J. Public Health* **112**, 734–735 (2022).

13. *Violence Against Educators and School Personnel: Crisis During COVID*. https://www.apa.org/education-career/k12/violence-educators.pdf (2022).

14. Devi, S. COVID-19 exacerbates violence against health workers. *Lancet* **396**, 658 (2020).

15. *Mental Health Atlas 2020*. 136 https://www.who.int/publications/i/item/9789240036703 (2021).

16. Behavioral Health Care in the United States: How It Works and Where It Falls Short. *The Commonwealth Fund* https://www.commonwealthfund.org/publications/explainer/2022/sep/behavioral-health-care-us-how-it-works-where-it-falls-short (2022) doi:10.26099/txpy-va34.

17. Aknin, L. B. *et al.* Policy stringency and mental health during the COVID-19 pandemic: a longitudinal analysis of data from 15 countries. *Lancet Public Health* **7**, e417–e426 (2022).

18. Chung, S. *et al.* Development of the Stress and Anxiety to Viral Epidemics-9 (SAVE-9) Scale for Assessing Work-related Stress and Anxiety in Healthcare Workers in Response to Viral Epidemics. *J. Korean Med. Sci.* **36**, e319 (2021).

19. HHS Announces $103 Million from American Rescue Plan to Strengthen Resiliency and Address Burnout in the Health Workforce. *U.S. Department of Health and Human Services* https://public3.pagefreezer.com/content/HHS.gov/30-12-2021T15:27/https://www.hhs.gov/about/news/2021/07/16/hhs-announces-103-million-arp-funding-to-address-health-workforce-burnout.html (2021).

20. COVID-19 Information Metrics for Response Leadership's Decision Making. *Centers for Disease Control and Prevention* https://www.cdc.gov/coronavirus/2019-ncov/global-covid-19/leadership-emergency-response.html (2020).