Travel Medicine and Infectious Disease 40 (2021) 102004

Contents lists available at ScienceDirect

Travel Medicine and Infectious Disease

journal homepage: www.elsevier.com/locate/tmaid

Original article

Proximity to international airports and early transmission of COVID-19 in the United States—An epidemiological assessment of the geographic distribution of 490,000 cases

Aastha Chokshi [a,*], Michelle DallaPiazza [a], Wei Wei Zhang [b], Ziad Sifri [b]

[a] Rutgers New Jersey Medical School, Department of Medicine, 185 S Orange Ave, Newark, NJ, 07103, USA
[b] Rutgers New Jersey Medical School, Department of Surgery, 185 S Orange Ave, Newark, NJ, 07103, USA

A R T I C L E I N F O

Keywords:
Covid-19
Containment
Hotspots
Public health interventions

A B S T R A C T

Background: Identifying hotspots in a pandemic is essential for early containment. In the context of the rapid global dissemination of the Covid-19 pandemic, describing viral infection rates in relation to international air travel early during the pandemic can help inform future public health policy. The objective of this study is to determine whether proximity to an international airport predicted higher infection rates during the early phase of the Covid-19 pandemic in the United States (US).
Methods: In this cross-sectional study, the authors examined the incidence of Covid-19 in areas near US international airports in the first weeks after detection of Covid-19 in all 50 states, using publicly available county-level incidence of Covid-19 data. They performed a multiple regression to determine the relative effects of population density and air traffic in the Counties Containing Airports (CCA) and the number of Covid-19 cases, and determined the odds of Covid-19 in CCA compared to the rest of the state.
Results: Multiple regression analysis revealed that air traffic was significantly correlated with Covid-19 cases during the initial phase of pandemic while population density was not significantly correlated. Three weeks into the pandemic, the pooled odds of Covid-19 cases in CCA was 2.66 (95% CI [2.64, 2.68], $p < 0.0001$).
Conclusions: The counties in the US containing international airports represented initial hotspots for Covid-19 transmission. Early public health containment efforts focused on these areas may help mitigate disease transmission during future similar novel respiratory virus epidemics.

1. Introduction

Since it was first identified in Wuhan, China in December 2019, Covid-19, caused by the novel coronavirus SARS-CoV-2, has become a global pandemic with over 1.4 million deaths globally as of November 30, 2020 [1]. The first case of Covid-19 in the United States (US) was identified on January 20, 2020 in Seattle, Washington [2]. By March 17, all 50 states reported cases [3]; and by April 10, 2020, 3 weeks into the outbreak, the US had a total of 492,416 cases and had entered the exponential growth phase secondary to community spread [3–5]. Community spread is an indicator of large-scale local transmission, and is a significant cause for concern due to untraceable infection sources, impeding effective contact tracing [6]. Early identification of hotspots can help to prioritize public health measures, such as contact tracing and increased testing, in these areas in an effort to mitigate community spread.

International travel is considered to be an important factor for introducing novel respiratory pathogens throughout the world [7–9]. During the H1N1 outbreak, studies performed in Iceland demonstrated the key role of international airports in the spread of disease [10]. A 2016 systematic review showed that air transportation accelerated influenza propagation [11]. In the context of the Covid-19 pandemic, studies have implicated the role of air travel as being a key factor for transmission in the early phase of the pandemic [12]. Describing the role of international airports on infection rates early in the course of the Covid-19 pandemic can help inform future public health policy focused on contact tracing and mitigation. This study aims to investigate the role of international airport traffic in establishing early hotspots for Covid-19

* Corresponding author.
E-mail addresses: acc224@njms.rutgers.edu (A. Chokshi), mld229@njms.rutgers.edu (M. DallaPiazza), wz280@njms.rutgers.edu (W.W. Zhang), sifrizi@njms.rutgers.edu (Z. Sifri).

https://doi.org/10.1016/j.tmaid.2021.102004
Received 1 July 2020; Received in revised form 20 December 2020; Accepted 22 February 2021
Available online 26 February 2021
1477-8939/

in US. Additionally, we aimed to determine the degree to which there was an increased risk of Covid-19 in areas with high airport traffic during the early phases of viral spread in the US.

2. Methods

We referenced data from the Bureau of Transportation Statistics to determine the 50 international airports in the US with the highest number of passenger enplanements, including both domestic and international travel [13,14].

Since all states reported Covid-19 cases by county, we performed our analysis at the county level, focusing our analysis on the 50 Counties Containing Airports (CCA) of interest. First, we performed a multiple regression looking at the relative effects of population density and air traffic in each of these counties on the number of Covid-19 cases. We determined the air traffic for each of the international airports included in the analysis by the number of passenger enplanements [13]. We obtained the population density of the CCA from the 2019 census data [15], and the number of Covid-19 cases in the CCA from state government websites as of April 10, 2020 [16–38]. We performed multiple regression analysis using Microsoft Excel.

Next, in order to investigate whether areas near international airports were associated with an increased incidence of Covid-19, we calculated the odds ratio of Covid-19 in CCA compared to the rest of the state. We determined the number of non-Covid-19 controls in each county by subtracting the Covid-19 cases from the county population. We determined the individual and pooled odds ratios using the Mantel-Haenszel method under the fixed effect model. We considered all of the NYC counties (Queens, Bronx, Manhattan, Kings, Nassau, Westchester, Suffolk, and Richmond) as CCA since the airports in New York City serve all of these areas. We used Microsoft excel and MedCalc softwares for data analysis.

We subsequently repeated the odds ratio computation for all of the states included in the analysis using Covid-19 cases as of November 29, 2020, to evaluate the change in odds ratios over time throughout the pandemic. We calculated the individual and pooled odds ratios as above.

3. Results

3.1. Multiple regression

Supplemental Table 1 summarizes the 50 international airports with the highest number of passenger enplanements and international visitors by state. The 50 international airports identified were located across 23 states. The average enplanements across all 50 international airports was 15,530,327 passengers annually, and ranged from 3.9 million to 51.8 million passengers annually across the 50 airports. In all states except New York, air traffic was found to have a statistically significant correlation with Covid-19 cases ($p = 0.004$) with a positive correlation coefficient of 95.75 while population density was found to be uncorrelated with Covid-19 cases in the early phase of the pandemic ($p = 0.377$) with a correlation coefficient of 0.10. Figs. 1 and 2 demonstrate scatter plots showing the correlation between air traffic and Covid-19 cases and the correlation between population density and Covid-19 cases respectively. However, including New York, we found that population density was significantly correlated with Covid-19 cases.

3.2. April 10, 2020 - Covid-19 incidence in CCA compared to rest of the state

The pooled odds of Covid-19 cases in CCA compared to all other counties in the state was 2.66 (95% CI [2.64, 2.68], $p < 0.0001$) and ranged from 0.79 to 4.62 for CCA within individual states (Fig. 3). Table 1 shows representative odds ratio calculations for CCA in California. The odds ratios of Covid-19 in CCA compared to the rest of the state were greater than 1.0 and significant at the 95% confidence level

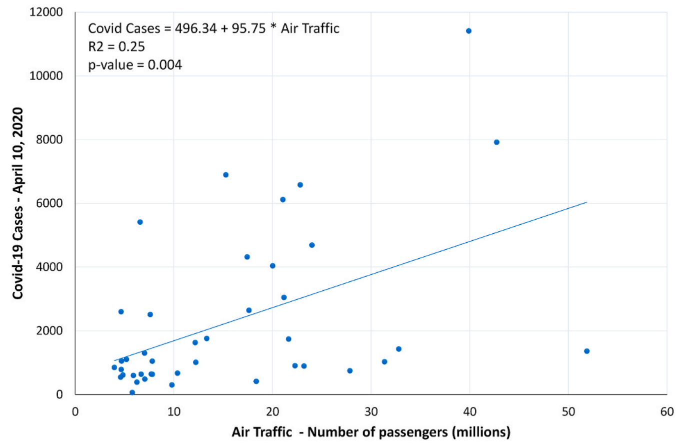

Fig. 1. Scatter Plot Representing Correlation Between Air Traffic and Covid-19 Cases. Air Traffic and Covid-19 cases are significantly correlated with p-value of 0.004 per multivariable regression and correlation coefficient of 95.75.

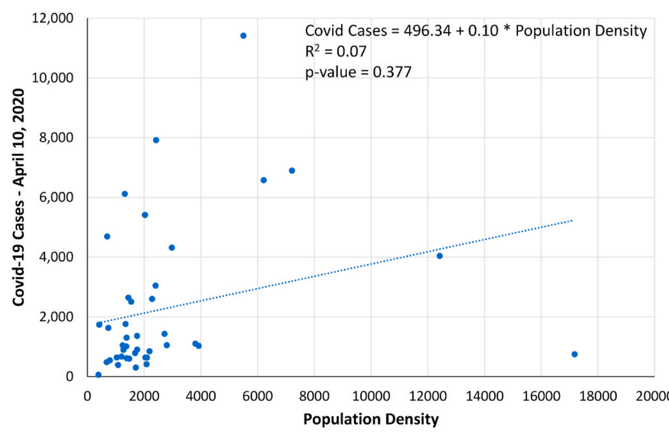

Fig. 2. Scatter Plot Representing Correlation Between Population Density and Covid-19 Cases. Population Density and Covid-19 cases are not significantly correlated with p-value of 0.377 per multivariable regression and correlation coefficient of 0.10.

($p < 0.05$) for 22 out of 23 (96%) states. The five states with the highest odds of Covid-19 in CCA were New York (4.62, 95% CI [4.56, 4.69], $p < 0.0001$), Louisiana (4.32, 95% CI [4.18, 4.46], $p < 0.0001$), Missouri (4.18, 95% CI [3.90, 4.48], $p < 0.0001$), Indiana (3.62, 95% CI [3.45, 3.80], $p < 0.0001$), and Illinois (3.33, 95% CI [3.23, 3.45], $p < 0.0001$). Arizona, with an odds ratio of 0.79, 95% CI [0.74, 0.85], $p < 0.0001$, was the only state with an odds ratio of less than 1.0.

3.3. November 29, 2020 - Covid-19 incidence in CCA compared to rest of the state

The pooled odds of Covid-19 infection in CCA compared to all other counties in the state was 1.067 (95% CI [1.065, 1.068], $p < 0.001$) and ranged from 0.579 to 1.849 for CCA within individual states (Fig. 4). The odds ratios are lower in November in all 23 states compared to the odds ratios computed as of April 10, 2020.

4. Discussion

In this population-based study using county-level Covid-19 and air traffic data, we found air traffic to be significantly correlated with the number of Covid-19 cases in the early phase of the pandemic. We also found significantly elevated odds of Covid-19 reported cases in counties in close proximity to the 50 busiest US international airports in the first

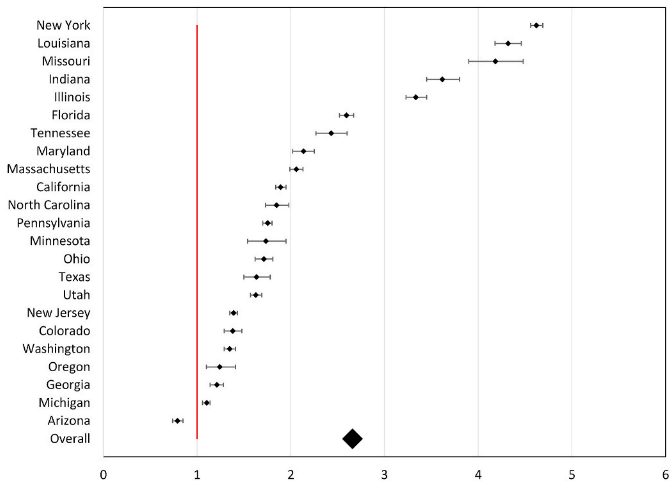

Fig. 3. Forest plot showing odds ratios of Covid-19 in Counties Containing Airports (CCA) Compared to the Rest of the State as of April 10, 2020. For each state, the odds ratio of Covid-19 in CCA compared to the rest of the state is shown by the diamond (◆) and the 95% confidence interval is depicted using the error bars. The overall odds ratio of Covid-19 in CCA compared to all other areas in the 23 states is shown by the large black diamond. The red line indicates an odds ratio of 1.0. Odds ratios not overlapping 1.0 are significant with a p-value$<$0.0001. These odds ratios are calculated based on April 10, 2020 Covid-19 cases. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

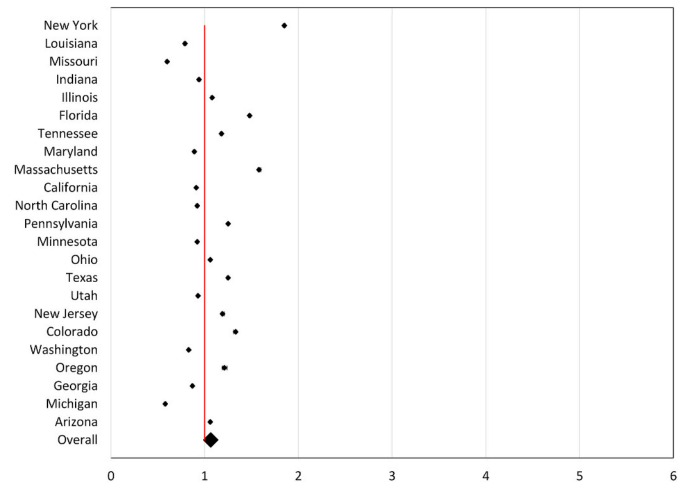

Fig. 4. Forest plot showing odds ratios of Covid-19 in Counties Containing Airports (CCA) Compared to the Rest of the State as of November 29, 2020. For each state, the odds ratio of Covid-19 in CCA compared to the rest of the state is shown by the diamond (◆) and the 95% confidence interval is depicted using the error bars. The overall odds ratio of Covid-19 in CCA compared to all other areas in the 23 states is shown by the large black diamond. The red line indicates an odds ratio of 1.0. These odds ratios are calculated based on November 29, 2020 Covid-19 cases. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Odds ratio of Covid-19 in counties containing airports within California as of April 10, 2020.

	Population	Covid-19 Cases	Non-Covid-19 Controls	Cases/1 M
California State	39,512,223	19,472	39,492,751	117.51
Counties Containing International Airports (CCA)				
Los Angeles county	10,039,107	7,919	10,031,188	789
San Francisco county	881,549	748	880,801	849
San Diego county	3,338,330	1,630	3,336,700	488
Santa Clara county	1,927,852	1,301	1,926,551	675
Alameda county	1,671,329	641	1,670,688	384
Sacramento county	1,552,058	601	1,551,457	387
Orange county	3,175,692	1,105	3,174,587	348
Total of Above 7 Counties	22,585,917	13,945	22,571,972	617
Counties in Rest of the State	16,926,306	5,527	16,920,779	327

Odds Ratio Covid-19 in CCA compared to Rest of the State: 1.89 (95% CI [1.84, 1.95], $p < 0.0001$).

few weeks after spread of Covid-19 to all 50 states.

Previously, studies have linked the volume of international travel to the viral transmission of yellow fever, dengue, and influenza [39–41]. A study on factors affecting Covid-19 cases demonstrated the role of air traffic, testing numbers, and population density in Covid-19 cases, with population density being a significant factor in places with persistently high Covid-19 cases rather than in the initial phase [12]. Our multiple regression analysis looked at population density and air traffic and their effect on total Covid-19 cases as of April 10, 2020. Our regression analysis supports the role of air traffic in the early phase of the pandemic while population density is not a significant factor affecting the number of Covid-19 cases in the early phase of the pandemic in all states except New York. When New York is included in the multiple regression model, population density is a more significant factor. This is likely because New York, which was the first epicenter of Covid-19 in the United States, entered community transmission phase much earlier than other states and therefore population density was a bigger influencing variable than air traffic, consistent with prior studies.

While the amount of testing is one of the key factors affecting number of Covid-19 cases, unfortunately there are no data available at the county level describing the amount or availability of testing in early April, so this data could not be included in our analysis. Population demographics may be another factor affecting Covid-19 cases. A simulation study on influenza pandemic suggested that the population demographics such as average household size, age, and per capita income, but not population density, were key factors of viral transmission in hotspots [42]. However, studies focusing on Covid-19 have shown that population demographics such as gender, ethnicity, poverty, and access to care did not affect the number of Covid-19 cases [12].

Overall, among states with high-volume international airports, our study shows 2.66 times increased pooled odds of Covid-19 in CCA compared to rest of the state in April 2020, three weeks after Covid-19 was detected in all 50 states in the US. We found significantly increased odds of Covid-19 in CCA compared to the rest of the state in 96% of states analyzed. Arizona was the only state with an odds ratio less than 1.0 in CCA compared to the rest of the state. One potential explanation for these results could be related to tourism in areas remote from international airports. In Arizona, for example, Coconino County, which contains the Grand Canyon, had an increased number of cases of Covid-19 compared to other counties in Arizona. The 2014 measles outbreak associated with Disneyland, California also supports the idea that US residents in areas surrounding tourist attractions and airports with high volume of international visitors have an increased risk of exposure to infectious diseases [43].

While international travel and proximity to international airports play a significant role in the early phase of the pandemic, once community transmission is established, they no longer play as significant of a role. In our analysis, the pooled odds ratio of 2.66 in April 2020 fell to 1.06 for Covid-19 in CCA compared to the rest of the state in November 2020. This supports the idea that proximity to international airports represents a significant factor for identifying hotspots early in a pandemic.

This study has several strengths. Firstly, by conducting a multiple regression, we investigated the relative effects of airports as well as population density, which are both implicated in Covid-19 transmission and found that population density is not significant influencing factor early on in the pandemic. Additionally, by looking at the top 50 international airports in the US, we were able to conduct a comprehensive study covering data from across 23 states, accounting for about 78% of the US population, and 87.5% of the Covid-19 cases in April 2020. We again repeated the odds ratio analysis using data from November 2020 when community spread was well-established. In this analysis, we found supporting evidence that while airports are predictive of early hotspots during a pandemic, other factors such as population density, lockdown measures, mask usage are likely more indicative of effects seen once community spread is established.

There are several limitations in this study. First, since many policies around testing, reporting, and social distancing were enacted at the state level, we compared counties within the same state and not between states. While comparing counties within the same state enabled us to control for differences in index cases and amount of testing, there may be differences in amount of testing between counties within the same state. Testing data is not reported at the county level in early phase of pandemic in March and April; therefore, we were not able to take testing levels into account. Additionally, we included airports in the study based on total enplanements—both international and domestic. However, despite the number of seasonally-adjusted passengers in February 2020 was the same as previous years the number of passengers dropped by 53% in March 2020 [44]. It would be helpful to determine the amount of travel change in each airport location to get additional insight into areas at increased risk of becoming local epicenters.

Our findings support the hypothesis that counties closest to international airports served as initial hotspots of Covid-19 transmission within the US [8,9]. This information is vital to guide initial public health measures with the goal of early containment and avoidance of broad lockdown measures, which lead to significant economic consequences. This information also helps prioritize initially limited testing resources to these high-risk areas, improving viral detection and mitigation of viral spread in the early phase of pandemic. Finally, identifying hotspots near international airports can assist in resource allocation early in the pandemic, as far as supplies for personal protective equipment, hospital support, and staffing considerations. The results of this study add to our understanding of early transmission in the US, and may help to guide public health policies to mitigate the spread of novel respiratory infections in future pandemics.

CRediT authorship contribution statement

Aastha Chokshi: Conceptualization, Methodology, Data curation, Writing – original draft. **Michelle DallaPiazza:** Writing – review & editing. **Wei Wei Zhang:** Writing – review & editing. **Ziad Sifri:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

We declare no competing interests.

Acknowledgements

No source of funding.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tmaid.2021.102004.

References

[1] Lewnard J, Lo N. Scientific and ethical basis for social-distancing interventions against COVID-19. Lancet Infect Dis 2020. https://doi.org/10.1016/s1473-3099(20)30190-0.
[2] Holshue M, DeBolt C, Lindquist S, et al. First case of 2019 novel coronavirus in the United States. N Engl J Med 2020;382(10):929–36. https://doi.org/10.1056/nejmoa2001191.
[3] Data API. The COVID tracking Project. 2020. https://covidtracking.com/api. [Accessed 9 May 2020].
[4] Coronavirus Update (live): 4,097,956 cases and 280,219 deaths from COVID-19 virus pandemic - worldometer. 2020. Worldometers.info, https://www.worldometers.info/coronavirus/. [Accessed 9 May 2020].
[5] Coronavirus disease (COVID-19) situation reports. WHO; 2020. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports. [Accessed 12 December 2020].
[6] Tiwari A, So M, Chong A, Chan J, Chu A. Pandemic risk of COVID-19 outbreak in the United States: an analysis of network connectedness with air travel data. Int J Infect Dis 2020. https://doi.org/10.1016/j.ijid.2020.11.143.
[7] coronavirus N, Epidemiology n. Epidemiological data from the nCoV-2019 outbreak: early descriptions from publicly available data. Virological 2020. http://virological.org/t/epidemiological-data-from-the-ncov-2019-outbreak-early-descriptions-from-publicly-available-data/337. [Accessed 10 May 2020].
[8] Kucharski A, Russell T, Diamond C, et al. Early dynamics of transmission and control of COVID-19: a mathematical modelling study. Lancet Infect Dis 2020;20(5):553–8. https://doi.org/10.1016/s1473-3099(20)30144-4.
[9] Bogoch I, Watts A, Thomas-Bachli A, Huber C, Kraemer M, Khan K. Pneumonia of unknown aetiology in Wuhan, China: potential for international spread via commercial air travel. J Trav Med 2020;27(2). https://doi.org/10.1093/jtm/taaa008.
[10] Kishore N, Mitchell R, Lash T, et al. Flying, phones and flu: anonymized call records suggest that Keflavik International Airport introduced pandemic H1N1 into Iceland in 2009. Influenza Other Respir Viruses 2019;14(1):37–45. https://doi.org/10.1111/irv.12690.
[11] Browne A, St-Onge Ahmad S, Beck C, Nguyen-Van-Tam J. The roles of transportation and transportation hubs in the propagation of influenza and coronaviruses: a systematic review. J Trav Med 2016;23(1). https://doi.org/10.1093/jtm/tav002.
[12] Roy S, Ghosh P. Factors affecting COVID-19 infected and death rates inform lockdown-related policymaking. PloS One 2020;15(10):e0241165. https://doi.org/10.1371/journal.pone.0241165.
[13] Passengers boarded at the top 50 U.S. Airports | Bureau of transportation Statistics. 2020. Bts.gov, https://www.bts.gov/content/passengers-boarded-top-50-us-airports. [Accessed 10 May 2020].
[14] International Visitation in the United States. Travel.trade.gov. 2020. https://travel.trade.gov/outreachpages/inbound.general_information.inbound_overview.asp. [Accessed 10 May 2020].
[15] U.S. Census Bureau. QuickFacts: New York city. New York: Census Bureau QuickFacts; 2020. https://www.census.gov/quickfacts/fact/table/newyorkcitynewyork/POP060210. [Accessed 10 May 2020].
[16] AZDHS | COVID-19 dashboards. Arizona Department of Health Services; 2020. https://www.azdhs.gov/preparedness/epidemiology-disease-control/infectious-disease-epidemiology/covid-19/dashboards/index.php. [Accessed 10 May 2020].
[17] COVID-19. Cdph.ca.gov. 2020. https://www.cdph.ca.gov/Programs/CID/DCDC/Pages/Immunization/ncov2019.aspx. [Accessed 10 May 2020].
[18] Case data | Colorado COVID-19 Updates. Covid19.Colorado.gov. 2020. https://covid19.colorado.gov/case-data. [Accessed 10 May 2020].
[19] Experience. Experience.arcgis.com. 2020. https://experience.arcgis.com/experience/96dd742462124fa0b38ddedb9b25e429/. [Accessed 10 May 2020].
[20] COVID-19 status report. Georgia Department of Public Health; 2020. https://dph.georgia.gov/covid-19-daily-status-report. [Accessed 10 May 2020].
[21] Coronavirus disease 2019 (COVID-19) | IDPH. Dph.Illinois.gov. 2020. http://www.dph.illinois.gov/topics-services/diseases-and-conditions/diseases-a-z-list/coronavirus. [Accessed 10 May 2020].
[22] ISDH. Novel coronavirus: novel coronavirus (COVID-19). 2020. In.gov, https://www.in.gov/isdh/28470.htm. [Accessed 10 May 2020].
[23] Louisiana Coronavirus COVID-19 Updated | Department of Health | State of Louisiana. Ldh.la.gov. 2020. http://ldh.la.gov/Coronavirus/. [Accessed 10 May 2020].
[24] Coronavirus - Maryland Department of Health. Coronavirus.Maryland.gov. 2020. https://coronavirus.maryland.gov/. [Accessed 10 May 2020].
[25] COVID-19 response reporting. Mass.gov. 2020. https://www.mass.gov/info-details/covid-19-cases-quarantine-and-monitoring. [Accessed 10 May 2020].
[26] Coronavirus - Michigan data. 2020. Michigan.gov, https://www.michigan.gov/coronavirus/0,9753,7-406-98163_98173—,00.html. [Accessed 10 May 2020].
[27] Situation Update for coronavirus disease 2019 (COVID-19) - Minnesota dept. Of health. 2020. Health.state.mn.us, https://www.health.state.mn.us/diseases/coronavirus/situation.html. [Accessed 10 May 2020].
[28] COVID-19 outbreak | health & Senior Services. 2020. Health.mo.gov, https://health.mo.gov/living/healthcondiseases/communicable/novel-coronavirus/results.php. [Accessed 10 May 2020].
[29] New Jersey COVID-19 Information Hub. Covid19.nj.gov. 2020. https://covid19.nj.gov/#live-updates. [Accessed 10 May 2020].
[30] Workbook: NYS-COVID19-Tracker. Coronavirus.health.ny.gov. 2020. https://coronavirus.health.ny.gov/county-county-breakdown-positive-cases. [Accessed 10 May 2020].

[31] NC DHHS COVID-19: COVID-19 North Carolina dashboard. 2020. Ncdhhs.gov, https://www.ncdhhs.gov/covid-19-case-count-nc. [Accessed 10 May 2020].
[32] COVID-19. Coronavirus.Ohio.gov. 2020. https://coronavirus.ohio.gov/wps/portal/gov/covid-19/. [Accessed 10 May 2020].
[33] Oregon Health Authority. COVID-19 updates. Oregon.gov; 2020. https://www.oregon.gov/oha/PH/DISEASESCONDITIONS/DISEASESAZ/Pages/emerging-respiratory-infections.aspx. [Accessed 10 May 2020].
[34] Pennsylvania COVID-19 numbers. Department of Health; 2020. https://www.health.pa.gov/topics/disease/coronavirus/Pages/Cases.aspx. [Accessed 10 May 2020].
[35] Novel coronavirus. Tn.gov. 2020. https://www.tn.gov/health/cedep/ncov.html. [Accessed 10 May 2020].
[36] ArcGIS. Dashboards. 2020. Txdshs.maps.arcgis.com, https://txdshs.maps.arcgis.com/apps/opsdashboard/index.html#/ed483ecd702b4298ab01e8b9cafc8b83. [Accessed 10 May 2020].
[37] COVID-19 surveillance in Utah. Utah Department of Health; 2020. https://coronavirus-dashboard.utah.gov. [Accessed 10 May 2020].
[38] COVID-19 data dashboard. Washington Department of Health; 2020. https://www.doh.wa.gov/Emergencies/NovelCoronavirusOutbreak2020COVID19/DataDashboard. [Accessed 10 May 2020].
[39] Brent S, Watts A, Cetron M, et al. International travel between global urban centres vulnerable to yellow fever transmission. Bull World Health Organ 2018;96(5):343–354B. https://doi.org/10.2471/blt.17.205658.
[40] Quam M, Khan K, Sears J, Hu W, Rocklöv J, Wilder-Smith A. Estimating air travel–associated importations of dengue virus into Italy. J Trav Med 2015;22(3):186–93. https://doi.org/10.1111/jtm.12192.
[41] Caley P, Becker N, Philp D. The waiting time for inter-country spread of pandemic influenza. PloS One 2007;2(1):e143. https://doi.org/10.1371/journal.pone.0000143.
[42] Stroud P, Del Valle S, Sydoriak S, Riese J, Mniszewski S. Spatial dynamics of pandemic influenza in a massive artificial Society. J Artif Soc Soc Simulat 2007;10. http://jasss.soc.surrey.ac.uk/10/4/9.html. [Accessed 10 May 2020].
[43] Measles outbreak—California, december 2014–february 2015. Ann Emerg Med 2015;66(1):82–3. https://doi.org/10.1016/j.annemergmed.2015.04.002.
[44] March 2020 U.S. Airline traffic data (final) | Bureau of transportation Statistics. Bts.gov; 2020. https://www.bts.gov/newsroom/march-2020-us-airline-traffic-data-final. [Accessed 12 December 2020].