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Socio-spatial influences on the prevalence of COVID-19 in central Pennsylvania

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1. Introduction

It has been well-demonstrated that social, geographic, and economic variance impact the rate of infectious disease transmission (Oestergaard et al., 2017; Khalatbari-Soltani et al., 2020; Gares et al., 2017; Doherty et al., 2007; Coffey et al., 2018; Rosenthal, 2009; McMichael, 2004). Socio-spatial influences that have historically contributed to the rapid spread of infections are poor hygiene (McMichael, 2004; Morse, 1995; Rao, 1998; Bula-Rudas et al., 2015; Hall, 2007), low income (McMichael, 2004; Rao, 1998; Relman and Choffnes, 2011; World Health Organization and UNICEF 2012; Farmer, 1996; Bonds et al., 2012), high population density (McMichael, 2004; Weiss and McMichael, 2004; Feigin and Christie, 1 May 2020), well-developed mass transit (Morse, 1995; Goscé and Johansson, 2018; Nasir et al., 2016), impaired host immunity (Farmer, 1996; Lederberg et al., 2003), malnutrition (Lederberg et al., 2003; Schaible and Stefan, 2007; Tomkins and Watson, 1989), and disadvantaged socioeconomic position (Khalatbari-Soltani et al., 2020). Additionally, centers of activity and commerce—such as shopping malls and superstores, bring together local and remote individuals. At the start of the coronavirus disease 2019 (COVID-19) pandemic, these locations in particular were highly trafficked as individuals sought to buy large volumes of goods and minimize travel. These circumstances create the opportunity for infectious diseases to disseminate (Ali and Keil, 2011; Kuebart and Stabler, 2020).

During the global outbreak of COVID-19, health systems tracked the viral spread and anticipated the projected surge of patients that could overwhelm their resources. They prepared by canceling non-emergent surgeries, restricting in-person office visits, and redeploying staff to areas of anticipated need. Some governments enacted stay-at-home orders and shut down all non-essential businesses. People were hopeful these actions would slow transmission. Unfortunately, there continued to be an exponential rise in the months following the first reported cases in December of 2019 (COVID, 2020).

In communities that were impacted early in the pandemic, there was a disparity in both diagnosis and mortality rates. These differences were noted in populations that have historically been socially and economically disadvantaged (Van Dorn et al., 2020). Additional studies demonstrated that air pollution (COVID, 2020) and environmental conditions (Van Dorn et al., 2020) were possible contributors to the severity and infection rate.

To identify, track, and mitigate the spread of COVID-19, spatial visualization with geographic information system (GIS) has been used (COVID, 2020; Wu et al., 2020; Wang et al., 2020; Mollalo et al., 2020; Boulos and Geraghty, 2020). GIS is a tool utilized to examine the spatial distribution of infectious diseases. It has aided clinicians and researchers in combating infection spread and improving patient care (Wu et al., 2020; Lakhani, 2020; Mollalo et al., 2019). During the COVID-19 pandemic, Mollalo et al. used GIS-based spatial modeling to analyze various factors at the county level to identify potential causes for spatial pattern discrepancy. They determined that median household income, percentage of nurse practitioners, and minority populations contributed to the high variance in disease incidence.

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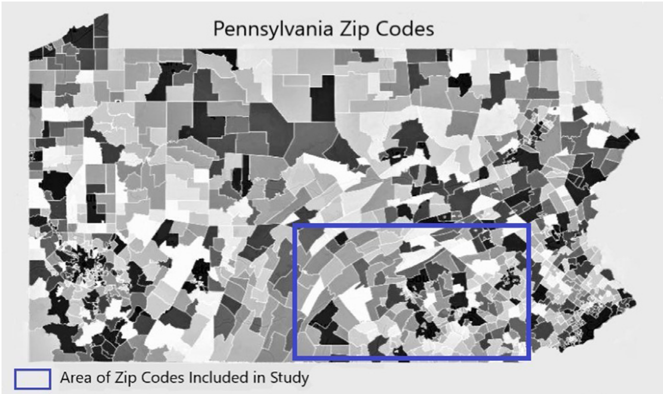

Fig. 1. Reference map of zip codes in Pennsylvania.

Identifying social, geographic, and economic factors that impact the incidence of COVID-19 will allow for the targeted allocation of limited resources available to hospitals, health systems, and governments. Additionally, this knowledge will help guide the safe relaxation of shutdowns and social gathering restrictions. The purpose of this study was to identify social, geographic, and economic factors that contributed to a higher prevalence of COVID-19.

2. Methods

2.1. Location description

Pennsylvania is a state in the mid-Atlantic region of the United States. The population is approximately 13 million persons, living in 2169 zip codes, seen in Figure 1. Penn State Milton S. Hershey Medical Center is a tertiary, research, and academic medical center located in central Pennsylvania. It is the only medical facility in Pennsylvania accredited as both an Adult and Pediatric Level 1 trauma center. Patients of the Penn State Medical Center come from over 796 zip codes representing a wide variety of rural and urban locales, including the state capital of Harrisburg.

2.2. Data collection

Penn State Health Institutional Review Board approved Study14977 under expedited review. Following approval, a retrospective review of all patients who tested positive for COVID-19 through Penn State Hershey Medical Center by viral PCR was conducted. Demographic data, hospital course, date of diagnosis, treatments provided, and outcomes were extracted from the electronic health record by the research team. Population, population density, median persons per household, and median household income for each patient zip code was obtained from the United States Census Bureau (Mollalo et al., 2019). To identify patients' composite social disadvantage, the community need index (CNI) was used (Lovett et al., 2014). CNI scores were obtained from Truven Health Analytics for each COVID patient's home zip code (United States Census Bureau 2020). Number of superstores was obtained from the Google map database and was verified with the Apple map database.

2.3. Data analysis

ArcGIS Desktop 10.7 (ESRI, Redwoods, CA) was used to visualize disease spread by zip codes in Pennsylvania. Data maps were created by plotting patient home zip code onto a predefined zip code map and measuring the density of patients per zip code. Maps were created biweekly for the preceding two weeks and the total number of COVID patients. Socioeconomic and population variables were added for each zip code, as noted above. An independent sample T-test was used to compare subgroup means. Chi-squared tests were used to compare categorical variables among the study cohort. A Pearson correlation was performed on each subgroup with the number of COVID-19 cases set as the dependent variable. One-way ANVOA testing was performed to identify differences in means among zip codes with superstores. The Tukey HSD was performed post hoc to determine which mean differences resulted in significance. Significant values were identified as those with $p < 0.05$.

3. Results

The first patient with COVID-19 was diagnosed at Penn State Health on March 17, 2020. There were 335 patients diagnosed over the next six weeks. Nineteen of these patients were less than 18 years old, and 316 were adults, with the average age being 47.4 (+/−19.5) years. One-hundred and ninety-nine (59.4%) of the patients were female. 8.4% were African-American, 17.9% were Asian, 48.5% were Caucasian, 20.4% were mixed race, 0.3% were Pacific Islander, and 4.5% were of unknown race. Ethnically, 19.2% of the patients were Hispanic/Latino, 9.0% were Nepalese, 6.3% were Islamic, 0.9% were Jewish, 0.6% were Russian, 0.6% were Vietnamese, 0.3% were Amish, and 63.1% did not specify an ethnicity. These patients lived in 67 unique zip codes. Seven were out of state or not identifiable and were excluded in subsequent analysis. These were visualized geographically at biweekly intervals, as demonstrated in Figure 2-4.

Of the 60 zip codes, the population ranged from 329 to 25 (23,721 +/- 22,928). The population density of these zip codes ranged from 56–2596 persons per square mile (1821 +/- 2907). The average household income ranged \$25,298-\$87,753 (61,145 +/- 14,274). The CNI scores ranged 1.4–4.8 (2.76 +/- 0.93). The average age per zip code as reported by the US Census ranged 22.5–51.6 (38.9 +/- 5.46). Number of persons per household ranged 1.22–3.00 75 (2.49 +/−0.26) (Table 1).

The number of superstores per zip code ranged from 0–4. Using the Pearson correlation coefficient, the number of COVID-19 positive patients significantly correlated with the number of superstores per zip code during the first four weeks ($R = 0.348$, $p = 0.007$) and the first six weeks ($R = 0.292$, $p = 0.024$) of community spread. During the first two weeks, there was not a significant relationship between superstores and COVID-19 positive patients. At no time, (two, four or six weeks) during community spread did the number of COVID-19 positive patients significantly correlate with total population ($p = 0.543$, 0.878, 0.865), population density ($p = 0.435$, 0.643, 0.816), median household income ($p = 0.143$, 0.192, 0.653), Age ($p = 0.234$, 0.602, 0.561), CNI score ($p = 0.522$, 0.602, 0.835), or persons per household ($p = 0.526$, 0.231, 0.302) in each zip code (Table 2).

A one-way ANOVA was conducted to compare the effect of the number of superstores per zip code on the number of positive COVID-19 cases at 2, 4, and 6 weeks. There was a significant difference at four weeks ($p = 0.009$) and six weeks ($p = 0.024$). In post hoc Tukey HSD, at four weeks, zip codes with four superstores had significantly more patients than those with 0,1, and 3 ($p = 0.004$, 0.031,0.041). At six weeks, there continued to be a significant difference ($p = 0.021$) between zip codes with no superstores and zip codes with 4. On average, at six weeks, zip codes with four superstores produced 12 more patients than those with none (Tables 3 and 4).

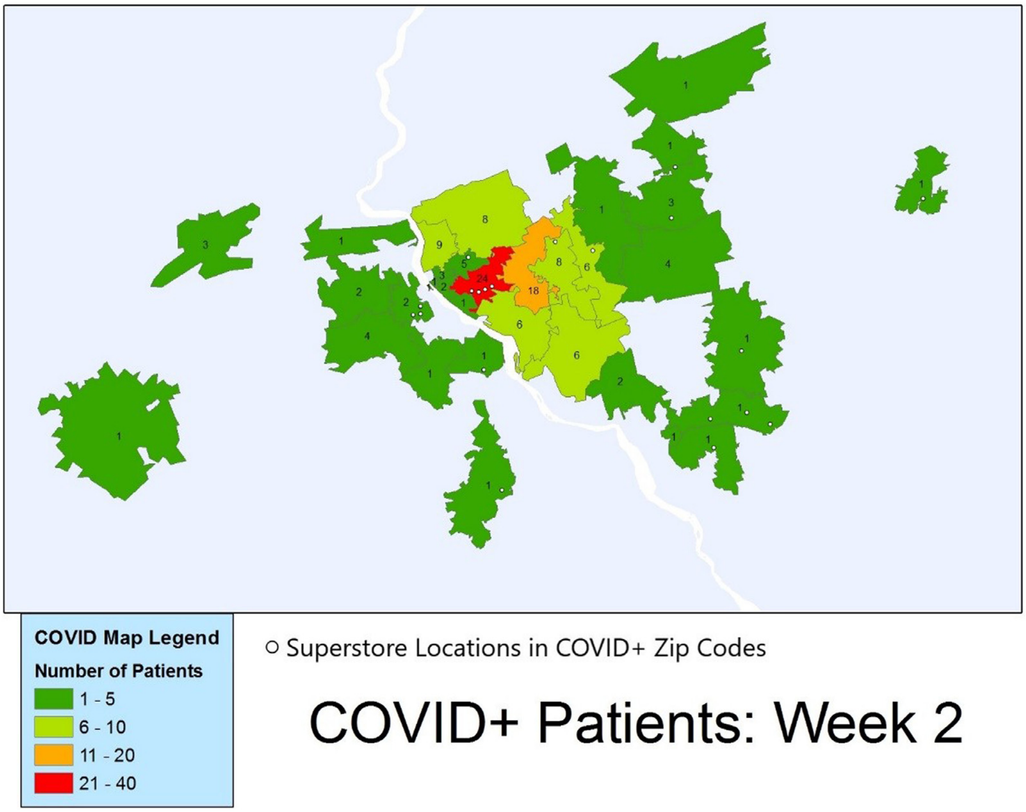

Fig. 2. COVID-19 Positive patients at Penn state Hershey as of week 2.

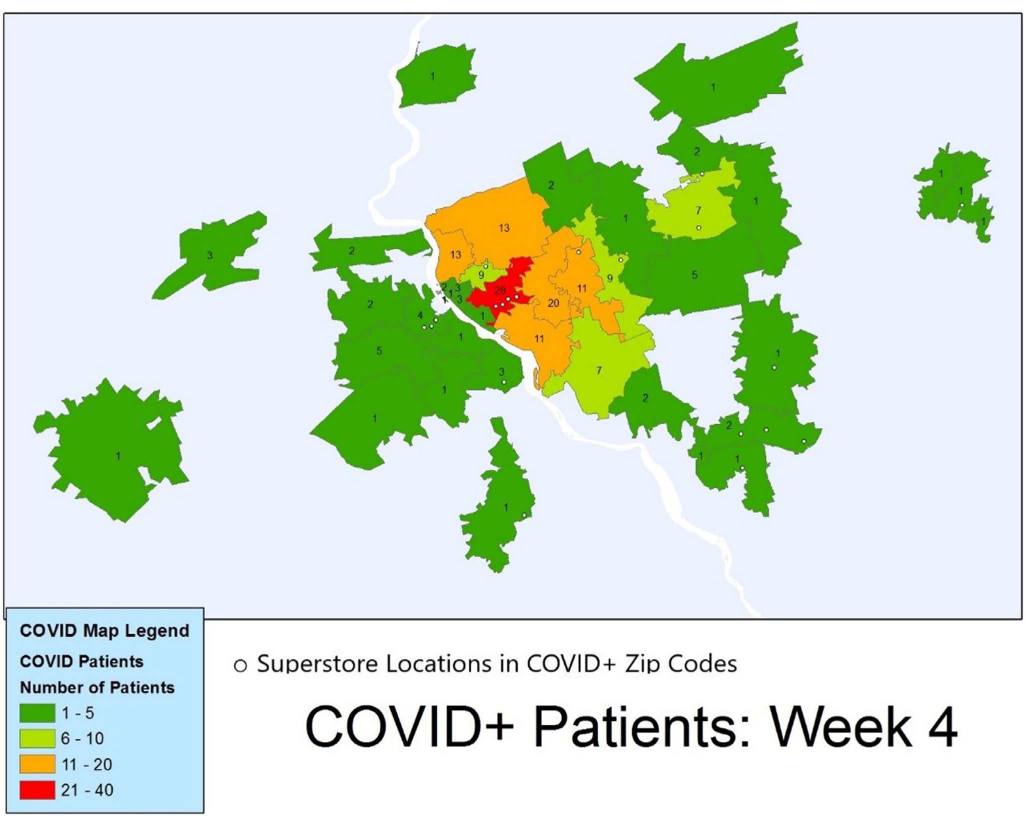

Fig. 3. COVID-19 positive patients at Penn State Hershey as of week 4.

Table 1
Zip code descriptive statistics.

	Population (Persons)	Population Density (Persons per sq. mile)	Average Household Income (US Dollars)	Community Need Index (CNI)	Average Age (Years)	Persons per Household
Mean for All Zip Codes	23,721	1821	$61,145	2.76	38.9	2.49
Standard Deviation for All Zip Codes	22,928	2907	$14,274	0.93	5.46	0.26
Minimum for All Zip Codes	329	56	$25,298	1.40	22.5	1.22
Maximum for All Zip Codes	157,725	12,596	$87,753	4.80	51.6	3.00

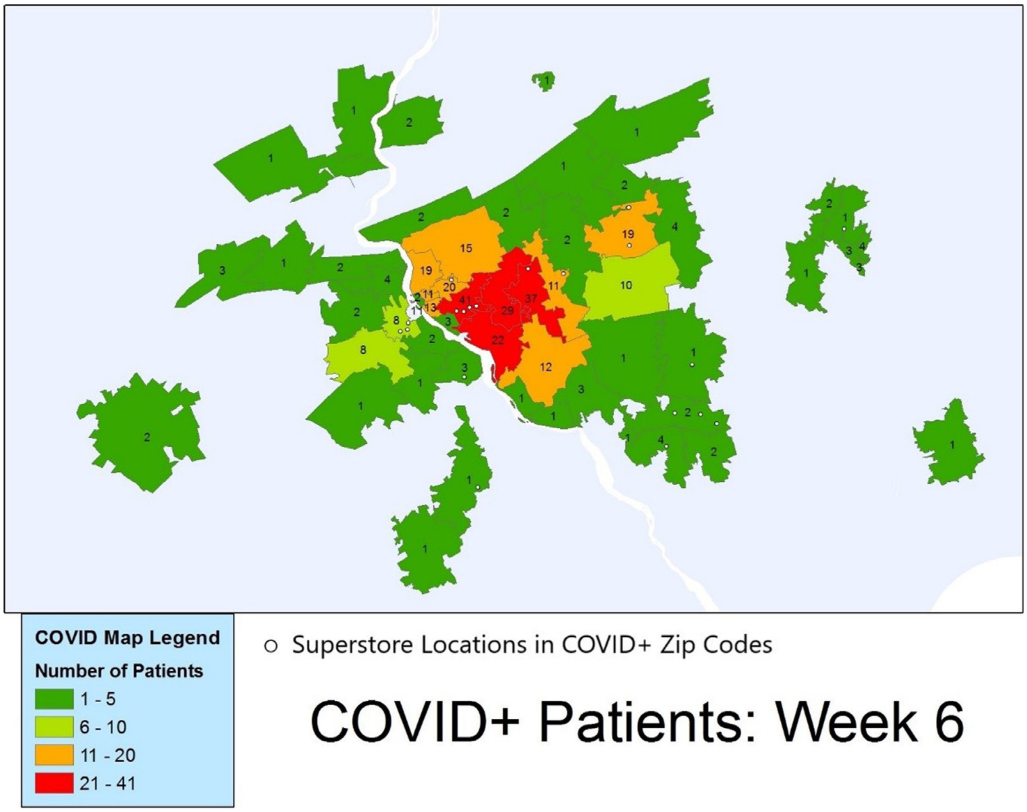

Fig. 4. COVID-19 positive patients at Penn State Hershey as of week 6.

Table 2
Pearson correlation results.

		COVID-19 POSITIVE PATIENTS—WEEK 2	COVID-19 POSITIVE PATIENTS—WEEK 4	COVID-19 POSITIVE PATIENTS—WEEK 6
Population	Pearson Correlation	.080	.022	.022
	Significance (Two-tailed)	.543	.868	.865
Population Density	Pearson Correlation	−0.103	−0.061	−0.031
	Significance (Two-tailed)	.435	.643	.816
Average Household Income	Pearson Correlation	.191	.171	.059
	Significance (Two-tailed)	.143	.192	.653
Average Age	Pearson Correlation	.156	.139	.077
	Significance (Two-tailed)	.234	.289	.561
Community Need Index (CNI)	Pearson Correlation	−0.084	−0.069	.028
	Significance (Two-tailed)	.522	.602	.835
Persons Per Household	Pearson Correlation	−0.083	−0.157	−0.135
	Significance (Two-tailed)	.526	.231	.302
Number of Superstores	Pearson Correlation	.152	.348	.292
	Significance (Two-tailed)	.247	.007	.024

4. Discussion

Previous research has demonstrated that social, geographic, and economic factors impact health and the spread of infectious disease (World Health Organization and UNICEF 2012). During the COVID-19 pandemic in 2019–2020, social distancing practices were recommended to prevent disease spread. These practices successfully reduced the incidence in prior pandemics and stopped disease spread in communities infected early in the COVID-19 pandemic (Roth and Barsi, 2005; Health, 2020; Reluga, 2010; Glass et al., 2006). It was recommended to limit commerce, travel, and gatherings to essential business, and individuals were instructed to maintain self-isolation during the early COVID-19 pandemic (Lim et al., 2013). the state of Pennsylvania shut down all

Table 3
Results of One-way ANOVA.

		Sum of Squares	Degrees of Freedom	Mean Square	F	Significance
2 Week Positive	Between Groups	3.9177	4	.979	1.324	.272
	Within Groups	40.667	55	.739		
	Total	44.583	59			
4 Week Positive	Between Groups	314.490	4	78.622	3.731	.009
	Within Groups	1158.910	55	21.071		
	Total	1473.400	59			
6 Week Positive	Between Groups	732.647	4	183.162	3.071	.024
	Within Groups	3279.936	55	59.635		
	Total	4012.583	59			

Table 4
Results of Tukey HSD.

Dependent Variable	Superstores	Superstores	Mean Difference	Standard Error	Significance	95% Confidence Interval
Week 2	0	1	−0.410	.275	.573	[−1.19– 0.37]
		2	−0.718	.515	.634	[−2.17– 0.74]
		3	.282	.515	.982	[−1.17– 1.74]
		4	−0.718	.623	.778	[−2.48– 1.04]
	1	0	.410	.275	.573	[−0.37– 1.19]
		2	−0.308	.551	.980	[−1.86– 1.25]
		3	.692	.551	.718	[−0.86– 2.25]
		4	−0.308	.653	.990	[−2.15– 1.53]
	2	0	.718	.515	.634	[−0.86– 2.25]
		1	.308	.551	.980	[−1.25−1.86]
		3	1.000	.702	.615	[−0.98−2.98]
		4	.000	.785	1.000	[−2.21−2.21]
	3	0	−0.282	.515	.982	[−1.74−1.17]
		1	−0.692	.551	.718	[−2.25−0.86]
		2	−1.000	.702	.615	[−2.98−0.98]
		4	−1.000	.785	.708	[−3.21−1.21]
	4	0	.718	.623	.778	[−1.04−2.48]
		1	.308	.653	.990	[−1.53−2.15]
		2	.000	.785	1.000	[−2.21−2.21]
		3	1.000	.785	.708	[−1.21– 3.21]
Week 4	0	1	−1.846	1.470	.719	[−5.99−2.30]
		2	−2.513	2.750	.890	[−10.27−5.24]
		3	−0.179	2.750	1.000	[−7.94−7.58]
		4	−12.346*	3.328	.004	[−21.73− (−2.96)]
	1	0	1.846	1.470	.719	[−2.30−5.99]
		2	−0.667	2.940	.999	[−8.96−7.63]
		3	1.667	2.940	.979	[−6.63– 9.96]
		4	−10.500*	3.487	.031	[−20.33− (−0.67)]
	2	0	2.513	2.750	.890	[−5.24−10.27]
		1	.667	2.940	.999	[−7.63– 8.96]
		3	2.333	3.748	.971	[−8.24−12.90]
		4	−9.833	4.190	.146	[−21.65−1.98]
	3	0	.179	2.750	1.000	[−7.58−7.94]
		1	−1.667	2.940	.979	[−9.96−6.63]
		2	−2.333	3.748	.971	[−12.90−8.24]
		4	−12.167*	4.190	.041	[−23.98−(−0.35)]
	4	0	12.346*	3.328	.004	[2.96−21.73]
		1	10.500*	3.487	.031	[0.67−20.33]
		2	9.833	4.190	.146	[−1.98−21.65]
		3	12.167*	4.190	.041	[0.35−23.98]
Week 6	0	1	−4.333	2.473	.412	[−11.31−2.64]
		2	−2.179	4.627	.990	[−15.23−10.87]
		3	.821	4.627	1.000	[−12.23−13.87]
		4	−17.679*	5.599	.021	[−33.47−(−1.89)]
	1	0	4.333	2.473	.412	[−2.64−11.31]
		2	2.154	4.946	.992	[−11.80−16.10]
		3	5.154	4.946	.835	[−8.80−19.10]
		4	−13.346	5.866	.169	[−29.89−3.20]
	2	0	2.179	4.627	.990	[−10.87−15.23]
		1	−2.154	4.946	.992	[−16.10−11.80]
		3	3.000	6.305	.989	[−14.78−20.78]
		4	−15.500	7.050	.196	[−35.38−4.38]
	3	0	−0.821	4.627	1.000	[−13.87−12.23]
		1	−5.154	4.946	.835	[−19.10−8.80]
		2	−3.000	6.305	.989	[−20.78−14.78]
		4	−18.500	7.050	.080	[−38.38−1.38]
	4	0	17.679*	5.599	.021	[1.89−33.47]
		1	13.346	5.866	.169	[−3.20−29.89]
		2	15.500	7.050	.196	[−4.38−35.38]
		3	18.500	7.050	.080	[−1.38−38.38]

* The mean difference is significant at the 0.05 level.

nonessential businesses on March 16, 2020. Despite these guidelines and precautions, the virus continued to spread at an exponential rate. This study demonstrates that, in central Pennsylvania, COVID-19 was spread disproportionately, with specific zip codes demonstrating higher concentrations of new diagnosis over others.

The zip codes with the highest rate of new diagnoses showed no correlation with median household income, the number of persons per household, CNI scores, total population, population density, or age. However, during the first six weeks of community spread, the one significant socio-spatial factor correlated with an increased incidence of COVID-19 was the concentration of superstores per zip code. Superstores as a nidus for infection spread is not unexpected. They allow large numbers of individuals to congregate in a relatively small area with minimal to moderate ventilation. The design of the store and marketing techniques prompt patrons to touch items while considering a purchase (Lewnard and Lo, 2020). Shopping carts utilized in these stores have seating for small children, encouraging a family-friendly atmosphere that enables families to shop together. This, while convenient, increases disease transmission, as children have previously been demonstrated to be vectors of viral disease (Health, 2020; Adolph et al., 2020; Spence et al., 2014). Finally, with the large volume of customers, staff disinfection of carts and baskets is unreliable and provides another source for contact with viral contamination (McQuilkin, 2020; Auwaerter, 2020; Gerba and Maxwell, 2012).

It is noted that persons living in a zip code with a superstore may not shop there. However, the superstore's presence is a draw for other businesses such as smaller retail stores, gas stations, restaurants, and pharmacies to locate in proximity (Morris, 2011). Superstores are often close to highway networks. Thus increasing traffic and allowing non-local people to have quick access to the superstore and the surrounding businesses. At the onset of the COVID-19 pandemic, these businesses drew residents into public contact settings in their quest to obtain essential provisions.

The decrease in the significance at six weeks of community spread bears further discussion. The reason for this is likely multifactorial. First, with a higher concentration of positive cases in the community, the superstores were a less impactful driver of viral transmission. Assisted living facilities were not included in this analysis as the first positive patient from a facility was not identified until four weeks into community spread. However, after facility associated patients began testing positive, the prevalence of disease shifted from the original pattern. Secondly, as the community spread progressed, superstore leadership took measures to reduce contagion spread. They limited the number of persons allowed in the store at one time, mandated mask use, placed floor stickers to guide patrons on 6 feet of separation, cleansed carts between users, and increased cleansing of self-checkout modules between patrons. Finally, as awareness of the disease and its transmission patterns increased in the community, individuals following CDC guidelines took self-initiative to protect themselves when venturing to the store. These factors then limited the spread not only in the zip codes with superstores but also in the entire area serviced by Penn State Medical Center, as evidenced by a flattening the infection curve at that time.

A limitation of this study is the presence of three hospital systems in central Pennsylvania. Not all patients were tested for COVID-19 through Penn State Health. If a significant number of persons tested positive from different zip codes than was observed in this study, the results could be impacted. Of note, the visual map of cases per zip code posted to the Department of Health website was analogous to the maps created in this study. Further investigation of the statistical correlation and significance of the total number of cases would be a practical next step.

5. Conclusion

This study analyzed the relationship between early pandemic COVID-19 spread and socio-spatial factors that have historically contributed to disease prevalence. It was concluded that, in central Pennsylvania, there is a correlation between the concentration of COVID-19 cases and the geographic placement of superstores. If further investigation augments the knowledge gained in this initial study, early and aggressive protective measures by retailers are warranted, and their early implementation may be a factor in the future control of disease spread. Additionally, the concentration of superstores per zip code should be considered by health care providers and policymakers when determining guidance for relaxing social distancing practices.

References

Adolph, C., et al., 2020. Pandemic politics: timing state-level social distancing responses to COVID-19. medRxiv.

Ali, S.H., Keil, R., 2011. Networked Disease: Emerging Infections in the Global City, 44. John Wiley & Sons.

Auwaerter, P.G., 2020. Coronavirus COVID-19 (SARS-2-CoV). Johns Hopkins ABX Guide.

Bonds, M.H., Dobson, A.P., Keenan, D.C., 2012. Disease ecology, biodiversity, and the latitudinal gradient in income. PLoS Biol. 10 (12).

Boulos, M.N.K., and E.M. Geraghty. "Geographical tracking and mapping of coronavirus disease COVID-19/severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic and associated events around the world: how 21st century GIS technologies are supporting the global fight against outbreaks and epidemics." (2020): 1–12.

Bula-Rudas, F.J., Rathore, M.H., Maraqa, N.F., 2015. Salmonella infections in childhood. Adv. Pediatr. 62 (1), 29–58.

Coffey, P.M., Ralph, A.P., Krause, V.L., 2018. The role of social determinants of health in the risk and prevention of group A streptococcal infection, acute rheumatic fever and rheumatic heart disease: a systematic review. PLoS Negl. Trop. Dis. 12 (6), e0006577.

COVID, C.S.S.E. "Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), 2020." (19).

Doherty, I.A., Leone, P.A., Aral, S.O., 2007. Social determinants of HIV infection in the deep south. Am. J. Public Health 97 (3), 391 -391.

Farmer, P., 1996. Social inequalities and emerging infectious diseases. Emerg. Infect. Dis. 2 (4), 259–269 https://dx.doi.org/10.3201/eid0204.960402.

Feigin, R.D., Christie, A.B., 1 May 2020. Occupation and commerce. Encyclopædia Britannica. Encyclopædia Britannica, Inc. www.britannica.com/science/infectious-disease/Occupation-and-commerce.

Gares, V., Panico, L., Castagne, R., et al., 2017. The role of the early social environment on Epstein Barr virus infection: a prospective observational design using the Millennium Cohort Study. Epidemiol. Infect. 145, 3405–3412.

Gerba, C.P., Maxwell, S., 2012. Bacterial contamination of shopping carts and approaches to control. Food Prot. Trends 32 (12), 747–749.

Glass, R.J., et al., 2006. Targeted social distancing designs for pandemic influenza. Emerg. Infect. Dis. 12 (11), 1671.

Goscé, L., Johansson, A., 2018. Analysing the link between public transport use and airborne transmission: mobility and contagion in the London underground. Environ. Health 17 (1), 84.

Hall, C.B., 2007. The spread of influenza and other respiratory viruses: complexities and conjectures. Clin. Infect. Dis. 45 (3), 353–359.

Health D. Community Needs Index. In:2020.

Khalatbari-Soltani, S., et al., 2020. Importance of collecting data on socioeconomic determinants from the early stage of the COVID-19 outbreak onwards. J. Epidemiol. Commun. Health.

Kuebart, A., Stabler, M., 2020. Infectious diseases as socio-spatial processes: the Covid-19 outbreak in Germany. Tijdschr. voor Econo. Soc. Geogr. 111 (3), 482–496.

Lakhani, Ali., 2020. Which Melbourne metropolitan areas are vulnerable to COVID-19 based on age, disability and access to health services? Using spatial analysis to identify service gaps and inform delivery. J. Pain Symptom Manag..

Lederberg, Joshua, Hamburg Margaret, A., Smolinski, Mark S., 2003. Microbial Threats to Health: Emergence, Detection, and Response. National Academies Press.

Lewnard, J.A., Lo, N.C., 2020. Scientific and ethical basis for social-distancing interventions against COVID-19. Lancet Infect. Dis..

Lim, P.L., Lee, T.H., Rowe, E.K., 2013. Middle East respiratory syndrome coronavirus (MERS CoV): update 2013. Curr. Infect. Dis. Rep. 15 (4), 295–298.

Lovett, D.A., et al., 2014. Using geographical information systems and cartograms as a health service quality improvement tool. Spat. Spatiotemporal Epidemiol. 10, 67–74.

McMichael, A.J., 2004. Environmental and social influences on emerging infectious diseases: past, present and future. Philos. Trans. R. Soc. Lond. B Biol. Sci. 359 (1447), 1049–1058.

McQuilkin, P.A., 2020. COVID-19 in the Pediatric Population.
Mollalo, A., et al., 2019. A GIS-based artificial neural network model for spatial distribution of tuberculosis across the continental United States. Int. J. Environ. Res. Public Health 16 (1), 157.
Mollalo, A., Vahedi, B., Rivera, K.M., 2020. GIS-based spatial modeling of COVID-19 incidence rate in the continental United States. Sci. Total Environ., 138884.
Morris, M.A., 2011. Molecular Detection of Fecal-Bacterial Contamination On Grocery Shopping Cart Handles Within the Sacramento Region Diss..
Morse, S.S., 1995. Factors in the emergence of infectious diseases. Emerg. Infect. Dis. 1 (1), 7–15. doi:10.3201/eid0101.950102.
Nasir, Z.A., et al., 2016. Airborne biological hazards and urban transport infrastructure: current challenges and future directions. Environ. Sci. Pollut. Res. 23 (15), 15757–15766.
Oestergaard, L.B., Schmiegelow, M.D., Bruun, N.E., et al., 2017. The associations between socioeconomic status and risk of staphylococcus aureus bacteremia and subsequent endocarditis - a Danish nationwide cohort study. BMC Infect. Dis. 17, 589 –5895.
Rao, G.G., 1998. Risk factors for the spread of antibiotic-resistant bacteria. Drugs 55 (3), 323–330.
Relman, D.A., Choffnes, E.R., 2011. The Causes and Impacts of Neglected Tropical and Zoonotic Diseases: Opportunities For Integrated Intervention Strategies. National Academies Press.
Reluga, T.C., 2010. Game theory of social distancing in response to an epidemic. PLoS Comput. Biol. 6 (5).
Rosenthal, J., 2009. Climate change and the geographic distribution of infectious diseases. Ecohealth 6 (4), 489–495.
Roth, R., Barsi, E., 2005. The community need index. A new tool pinpoints health care disparities in communities throughout the nation. Health Prog. 86, 32–38.
Schaible, U.E., Stefan, H.E., 2007. Malnutrition and infection: complex mechanisms and global impacts. PLoS Med. 4 (5).
Spence, C., et al., 2014. Store atmospherics: a multisensory perspective. Psychol. Market. 31 (7), 472–488.
Tomkins, A., Watson, F., 1989. Malnutrition and infection: a review. Malnutrition Infect. Rev. 5.
United States Census Bureau. Zip Code Database. https://www.unitedstateszipcodes.org/about.php. Published 2020. Accessed May 2, 2020, 2020.
Van Dorn, A., Cooney, R.E., Sabin, M.L., 2020. COVID-19 exacerbating inequalities in the US. Lancet N. Am. Ed. 395 (10232), 1243–1244.
Wang, J., et al. "High temperature and high humidity reduce the transmission of COVID-19." Available at SSRN 3551767 (2020).
Weiss, R.A., McMichael, A.J., 2004. Social and environmental risk factors in the emergence of infectious diseases. Nat. Med. 10 (12), S70–S76.
World Health Organization, and UNICEF, 2012. Global Report for Research On Infectious Diseases of Poverty 2012. World Health Organization.
Wu, Xiao, et al., 2020. Exposure to air pollution and COVID-19 mortality in the United States. medRxiv.