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Impacts of Broadband and the Social Determinants of Health on COVID-19 Mortality and Infant Death Rates in EPA-Designated Technical Assistance Communities

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The University of Maryland, College Park
2018

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An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
in partial fulfillment of the requirements for the degree of
Master of Public Health
in Environmental Health
2021

Abstract

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Purpose: This study aims to externally validate the findings from a previous broadband project that assessed the lack of access to broadband/telemedicine and its effect on health disparities throughout rural Georgia (Ravichandran, 2020). The Georgia Broadband Project found poor broadband coverage linked, at a statistically significant level, to increased COVID-19 Deaths Per 100K Residents (COVID DR), as well as higher Infant Deaths Per 1K Live Births (IMR) (Ravichandran, 2020).

Methods: A total of 41 counties were chosen from the EPA's Office of Community Revitalization Technical Assistance (OCR TA) website, specifically from the Healthy Places for Healthy People and Cool & Connected programs (EPA, 2021). Due to the lack of granular reporting on COVID DR, COVID-19 Case Fatality Rate (CFR), and IMR, analyses were done at the county level, which presented a layer of unavoidable ecological bias. Each county was matched 1:2 with other counties in the same state with similar populations, to account for population density and mobility. This resulted in a total N = 123 counties to enter the analysis. Due to the non-normal nature of the aforementioned health outcomes of interest, spearman correlation assessments, two-sample-t-test hypothesis testing, and Poisson regression modeling were performed via Statistical Analysis Software (SAS) programming.

Results: The spearman correlations between broadband and the health outcomes were not strong nor significant. Based on the two-sample-t-tests, there was no statistical significance observed between OCR TA and non-OCR TA communities for the COVID DR and CFR (p-value = 0.9474 and 0.6870, respectively), though the former appears to possess significantly higher IMR (p-value = 0.0142). However, our secondary hypothesis of broadband being protective against the COVID health outcomes holds true based on the combination of the Two-Sample-T-Test (p-value = 0.0114) and the Simple Linear Regression Model (negative beta coefficient) with broadband as the predictor; however, it should be noted that the Two-Sample-T-Test did not portray significance for CFR or IMR (p-value = 0.3228 and 0.3550, respectively), though the point estimate displayed protection. Simple Poisson models for COVID DR exhibited a synergistic, protective relationship with broadband access, median household income, numeracy score, and literacy scores. An antagonist relationship was seen with the other predictors. All but EPA Designation (p-value = 0.6336) did not contain the null value for their respective beta coefficients. In terms of Simple Poisson models for COVID CFR, all of the beta coefficients contained the null (p-values ranged from 0.6875 to 0.9713) so judgements on synergistic vs. antagonistic qualities are not significant. Lastly, Simple Poisson models for IMR, revealed that median household income, urbanity, numeracy score, literacy score, and % foreign born were synergistic and protective, while poverty rate, minority presence, pandemic vulnerability score, EPA designation, SNAP, and % unemployed were all antagonistic.

Conclusions: The rise of COVID DR in broadband "deserts" compared to highly served areas further emphasizes the exigence for localized as well as federal broadband expansion initiatives. Due to rapid advances in technology, increased demand, and frequent adjustments to the Federal Communication Commission's (FCC) definition of broadband, the latter should be analogous to

the United States Rural Electrification Act (REA) of 1936, which expanded power to half of rural farmland. Because high speed and low latency networks are no longer considered luxuries but rather essential in the modern digital era, higher speed thresholds (> 100 mbps, 1gbps) should be utilized to prevent misclassification or underreporting bias in future broadband-related projects. Furthermore, the extensive effects of the social determinants of health as covariates presents a need to contextualize them within the broadband-health outcome pathway moving forward. Qualitative approaches, such as gathering first-hand residential insights via electronic data capturization tools and PhotoVoice, would corroborate the statistical analysis and aid in policymaking/agenda setting. These efforts can prompt effective interventions, as presented in Frieden's 5-Tiered Pyramid Framework for Public Health Action (Frieden, 2010)

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Acknowledgements

First, I would like to thank Mr. Michael Burns of the Community and College Partners Program (C2P2) for the opportunity to explore broadband as a primary exposure to health outcomes and for giving me the platform to present my findings to a diverse scientific audience. Additionally, I would like to thank him for connecting me with faculty from other universities, with whom I have been granted the wonderful opportunity to collaborate with on broadband-related research projects with the aim of spurring policy change and achieving other tangible goals. Immediate deliverables from these new partnerships will include PowerPoint Presentations to state policymakers and the development of manuscripts for publication in scientific journals with a focus on environmental justice and health disparities.

Second, I would like to thank Dr. Donghai Liang, my faculty advisor at the Gangarosa Department of Environmental Health, for his guidance along the statistical component of this study, ensuring that my statistical methods were valid and results were genuine. I would also like to thank him for taking time to meet with me regularly to ensure the smooth and timely development of this thesis.

Third, I extend gratitude to Dr. Margot Brown, my thesis field advisor, current AVP of the Environmental Defense Fund, and former Deputy Director of the EPA’s Office of Children’s Health Protection, for overseeing this project and proposing a need to explore infant mortality as a primary outcome of interest, in addition to COVID-19 mortality. I would also like to thank her for serving as my professional mentor and, like Mr. Burns, granting me prestigious platforms to promote my work to the scientific community.

Lastly, I am grateful for my professors at the Rollins School of Public Health (RSPH) at Emory University, namely those who taught the Research Design and Data Analysis courses, respectively, for adding a level of guidance and critique on elements of this project throughout its completion.

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1. Introduction

1.1 Broadband and Exigence for this Study

Broadband refers to high Internet speed offered in 4 forms: 1) Digital Subscriber Line (DSL) utilized by telephone wires 2) Cable provided by a local cable TV provider 3) Fiber Optic where infrared light transmits info between places via fibers and is the newest and fastest and 4) Satellite which is the slowest and most costly (FCC, 2014) (Ravichandran, 2020). All 4 forms of broadband are considered upgrades over the more archaic dial up system, which refers to the usage of a modem and physical dialing of a telephone number in order to connect to the Internet. In Table 1, the Federal Communications Commission (FCC) has outlined activities that can be performed at various broadband speeds (FCC, 2020).

Table 1: FCC Broadband Speed Guide w/ Key Select Activities

Broadband Speed (download)	Activity
~1 mpbs	• General Browsing and Email • Social Media • Standard Skype Call
3-4 mbps	• Streaming SD Video • Connecting Gaming Console to Internet
5-25 mbps	• Telecommuting • File Downloading • Streaming HD/ultra HD 4K Video HD Videoconferencing
50-100 mbps	• Telemedicine

1.2 What is COVID-19?

The Coronavirus Disease 2019 (COVID-19) was recognized in December 2019 after an outbreak in Wuhan, China. It presents a higher morbidity and mortality rate among older patients; however, the overall case fatality rate (CFR) varies but hovers ~2% (Fauci et al., 2020). Epidemiologists have estimated a reproduction number (R_0) of roughly 2.2, indicating that each infected person may spread the virus to about 2 additional people, raising alarm for densely populated communities (Fauci et al., 2020). COVID-19, unlike previous pandemics in recent history, has led to global lockdowns, mass cancellations of events like the 2020 Tokyo Olympics, and contributed to the largest economic recession observed since the Great Depression of the 1930s (Nicola et al., 2020).

1.3 COVID-19 and its Impacts on Medical Treatment

COVID-19 has shifted the dynamics of medical diagnosis and treatment from in-person to virtual telehealth platforms, the latter of which requires high speed, low latency broadband networks, upwards of 50-100 mbps downloadable speeds. In addition to the shift away from in-person care, there have been 8 hospital closures in rural Georgia in the last decade alone (Ellison, 2019). This touches on the 3 A's within the environmental justice (EJ) framework: accessibility, affordability, and availability (EPA, 2013). Not only do the hospital closures make healthcare less available, but the state of Georgia's rejection of the Medicaid expand option within the ACA has made it less accessible and affordability for many residents (KFF, 2020). Georgia has one of the highest uninsured rates in the country; thus, depleted broadband access during the COVID-19 pandemic is expected to present cumulative impacts, adding an EJ lens to this study (Miller, 2019). Bringing broadband to underserved areas can also spur economic growth, which has downstream benefits on human health (Frakt, 2018). Communities that include broadband initiative elements in their local planning proposals, such as is the case in Georgia, may receive broadband ready community designation. This label is lucrative for businesses, facilities, and technology to invest in the community (GBDI, 2018). There has been little prior research connecting broadband access to health outcomes, let alone COVID-19; thus the Community and College Partners Program (C2P2) conducted a pilot study specific to the state of Georgia, which revealed a strong correlation between broadband, COVID-19 Death Rate (COVID DR), and infant mortality rate (IMR) (Ravichandran, 2020). This piqued the interest of public health experts at various federal government agencies (i.e., Centers for Disease Control, Environmental Protection Agency) as well as faculty at other universities (Clemson, Grambling State, New Mexico State), with former

Deputy Director Margot Brown of the EPA's Office of Children's Health Protection ultimately serving as the thesis advisor for this project. These health personnel saw the need for exigence to externally validate these findings to a wider geographic region, prompting this research. By doing so, we can fill in the knowledge gaps on lurking variables that confound the relationship between more conventional environmental exposures with an emphasis on the built environment. This would enhance the field of social epidemiology by accentuating the role of the built environment on human health, and addressing the politics of public health.

1.4 Future of Telehealth

The general public is anxious about what the "new normal" brings in a post-COVID setting. Prior to the pandemic, only 11% of consumers used telehealth, compared to 76% who view it favorably moving forward (Henry, 2020). Similarly, 57% of providers view telehealth more favorably than they did pre-COVID and 64% are comfortable using the platform (Henry, 2020). Therefore, telehealth becomes a launching pad for practices such as: precision medicine, counseling, and treatment options all conducted over videoconferencing and secure portals. Even insurance companies are aligning virtual costs with in-person costs (America's Health Insurance Plans, 2021). Furthermore, companies view telehealth as an opportunity for growth and are doing their share in bridging the gap across the healthcare industry (Morey, 2020).

1.5 Importance of the Social Determinants of Health

According to the CDC, social determinants "such as poverty, unequal access to health care…and racism are underlying, contributing factors of health inequities" (CDC, 2019). The Rural Policy Research Institute (RUPRI) identified indicators of a high human service needs community, which included minority population and poverty rate. Literature has shown that low socioeconomic status (SES) is a key driver towards increased COVID-19 transmission, due to overcrowding and a need to work outside of home that makes it difficult to adhere to physical distancing measures, and other predictors associated with low median household income and poverty (Chen & Krieger, 2021) (Jay et al., 2020). In addition to COVID-19, other health outcomes such as premature death and diabetes prevalence can be attributed to the lack of medical facilities (Rollston & Galea, 2020). Granular to Georgia, large differences in diabetes rate, albeit not significant, were observed between hospital presence and diabetes prevalence (Ravichandran, 2020). However, strictly stratifying by rural vs. urban counties revealed a significant difference in mean diabetes prevalence. Values listed as % of residents [95% CI] were as follows: Rural = 15.83 (95% confidence interval [CI]: 14.64, 17.02) vs. Urban = 13.82 (95% CI: 12.41, 15.23). In Georgia, rural counties had a significantly lower presence of hospitals, an aging physician staff, and frequent hospital closures, compared to their urban counterparts (Ravichandran, 2020). These touch on cumulative impacts and EJ concepts such as "Double or Triple Jeopardy" (Meadows-Fernandez, 2020).

1.6 EPA's Technical Assistance Program

Through its Technical Assistance program, the U.S Environmental Protection Agency's (EPA) Office of Community Revitalization (OCR) has partnered with communities to provide smart growth intervention strategies. These communities are known as Technical Assistance (TA) communities and are part of various programs, such as Healthy Places for Healthy People (HP2) and Cool & Connected, the latter of which helps community representatives develop an action plan for using broadband to revitalize downtowns and spur economic opportunity (EPA, 2021). Eligible applicants for HP2 include: "local government representatives, health care facilities, local health departments, neighborhood associations, main street districts, nonprofit organizations, tribes, and others proposing to work in a neighborhood, town, or city located anywhere in the United States" (EPA, 2017). The EPA gives special consideration to communities that are economically distressed and underserved (EPA, 2017). Similarly, "any community representative is welcome to submit an application to participate in Cool & Connected (EPA, 2016). [The] community should have existing or anticipated broadband service that can be leveraged for community development" (EPA, 2016). The EPA gives special consideration to small towns and rural communities that face economic challenges and communities where the United States Department of Agriculture has provided loans and grants in support of broadband services (EPA, 2016). Figure 1 reveals the location of these TA communities and how this project can utilize them to represent a wider geographic region to externally validate the Georgia broadband study.

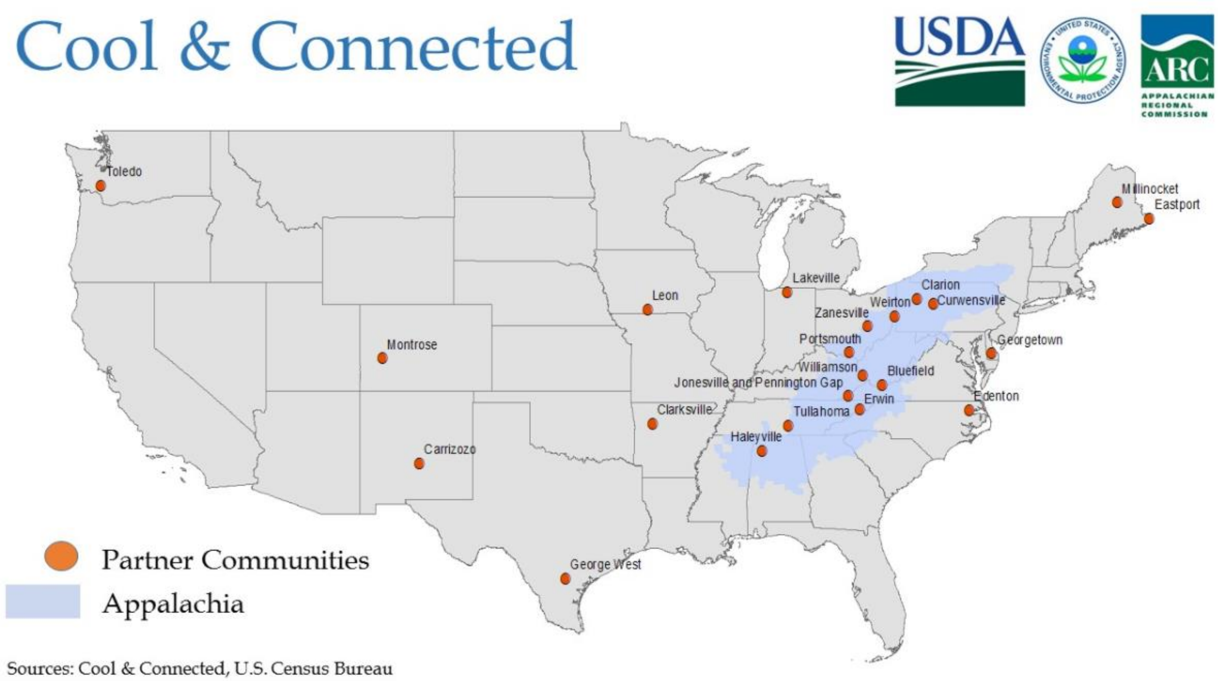

Figure 1A: Map of Technical Assistance Communities From Cool & Connected Partnership

Figure 1B: Map of Technical Assistance Communities From Healthy Places for Healthy People Partnership

2. Methods

2.1 Hypothesis

OCR TA communities will suffer from a disproportionate burden of COVID-19 and IMR. Regardless of designation, COVID DR, CFR, and IMR will be higher in low SES "broadband deserts," or communities that lack adequate internet capacity, assessed via hypothesis testing. We hypothesized that broadband would have a protective effect against adverse COVID outcomes, where negative effect coefficients will be observed for broadband in both the simple and parsimonious best fit models for COVID DR, CFR, and IMR.

2.2 Data Collection

2.2.1 Predictors

N = 41 OCR TA communities were selected from the EPA's Smart Growth website, with 82 control communities selected, matched on population density and state. This led to a total N = 123 observations (Table 2). Predictor and outcome data were collected from publicly available data sources and manually entered into an Excel Spreadsheet. Population estimates and median age of communities were acquired from the American Census Bureau, as of the year 2018. To remain consistent with methodology from the Georgia broadband study, median household income data was acquired from *City-data.com*. County type (rural vs. urban) was assessed via the Economic Research Service, a component of the United States Department of Agriculture and principal agency of the Federal Statistics System of the United States. Broadband coverage figures were obtained from *Broadbandnow.com*. The uninsured population referred to percentage under 65 years of age without health insurance and was acquired from the 2020 County Health Rankings report, which is derived from the US Census Bureau's Small Area Health Insurance Estimates (SAHIE) program.

Table 2: TA vs. Non-TA Communities by County and State

TA Communities		*Non-TA Communities*	
County, N = 41	*State, N = 41*	*County, N = 82*	*State, N = 82*
Sumter	Alabama	Crenshaw	Alabama
Hale	Alabama	Coosa	Alabama
Winston	Alabama	Geneva	Alabama
Marion	Alabama	Cherokee	Alabama
Santa Cruz	Arizona	Conecuh	Alabama
Johnson	Arkansas	Barbour	Alabama
Los Angeles	California	Monroe	Alabama
Montrose	Colorado	Choctaw	Alabama
Sussex	Delaware	Gila	Arizona
Madison	Indiana	Graham	Arizona
St. Joseph	Indiana	Cleburne	Arkansas
Decatur	Iowa	Ouachita	Arkansas
Powell	Kentucky	Orange	California
Avoyelles Parish	Louisiana	San Diego	California
Terrebonne Parish	Louisiana	Eagle	Colorado
Penobscot	Maine	Fremont	Colorado

Kennebec	Maine	New Castle	Delaware
Washington	Maine	Kent	Delaware
St. Clair	Missouri	Fountain	Indiana
Lawrence	Missouri	Allen	Indiana
Barry	Missouri	Vermillion	Indiana
Lincoln	New Mexico	Hamilton	Indiana
Halifax	North Carolina	Worth	Iowa
Chowan	North Carolina	Adair	Iowa
Scioto	Ohio	Breathitt	Kentucky
Muskingum	Ohio	Bath	Kentucky
Clarion	Pennsylvania	St. Bernard	Louisiana
Clearfield	Pennsylvania	Bossier	Louisiana
Unicoi	Tennessee	St. John the Baptist	Louisiana
Coffee	Tennessee	Ascension	Louisiana
Franklin	Tennessee	Lincoln	Maine
Live Oak	Texas	Hancock	Maine
Lee	Virginia	York	Maine
Chelan	Washington	Androscoggin	Maine
Lewis	Washington	Cumberland	Maine
Jefferson	Washington	Aroostook	Maine
Fayette	West Virginia	Scott	Missouri
Mercer	West Virginia	Grundy	Missouri
Brooke	West Virginia	Benton	Missouri
Hancock	West Virginia	Webster	Missouri
Mingo	West Virginia	Laclede	Missouri
		Ozark	Missouri
		Roosevelt	New Mexico
		Los Alamos	New Mexico
		Edgecomb	North Carolina
		Swain	North Carolina
		Hoke	North Carolina
		Mitchell	North Carolina
		Hancock	Ohio
		Tuscarawas	Ohio
		Ross	Ohio
		Erie	Ohio
		Indiana	Pennsylvania
		Warren	Pennsylvania
		Clinton	Pennsylvania
		Somerset	Pennsylvania
		Haywood	Tennessee
		Carter	Tennessee
		Warren	Tennessee
		Johnson	Tennessee
		Cumberland	Tennessee
		Lawrence	Tennessee
		Terry	Texas
		Red River	Texas
		Prince Edward	Virginia
		Lunenburg	Virginia
		Island	Washington
		Mason	Washington
		Douglas	Washington
		Clallam	Washington
		Grays Harbor	Washington
		Okanogan	Washington
		Jefferson	West Virginia
		Ohio	West Virginia
		Jackson	West Virginia
		Hampshire	West Virginia
		Boone	West Virginia
		Randolph	West Virginia

		Jackson	West Virginia
		Upshur	West Virginia
		Wayne	West Virginia
		Marion	West Virginia

In addition to the abovementioned predictors, the Program for the International Assessment of Adult Competencies (PIACC) was used for data on literacy and numeracy indirect estimate scores. Further supplementing the gathering of SDOH data, PIACC also contained % receiving SNAP benefits, % foreign born, and proportion of population aged 16-64 who are employed and unemployed.

2.2.2 Outcomes

COVID-19 mortality data was obtained from the National Institute of Environmental Health Sciences (NIEHS) Pandemic Vulnerability Index Map, timestamped: 10/12/2020. Figure 2 reveals the choropleth map for the entirety of the US, by COVID-19 Vulnerability Ranking. Vulnerability scores were calculated from an amalgamation of individual factors, including: transmissible cases, disease spread, population mobility, residential density, social distancing and testing interventions, population demographics, air pollution, age distribution, co-morbidities, health disparities, and hospital bed prevalence, all assessed “a priori” by NIEHS (NIEHS). IMRs were acquired from county health departments and county-level reports and reported as 3-5 year averages. In order to account for the general downward trend in infant deaths over time, only averages from 2011-present were assessed (Singh & Yu, 1995).

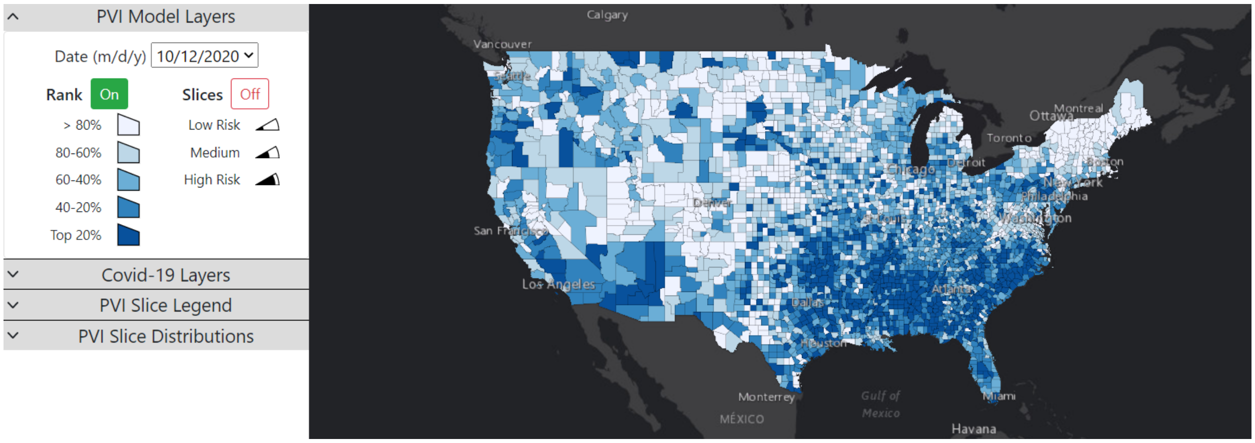

Figure 2: Choropleth Map of COVID-19 Vulnerability Index Scores by County in the United States

2.3 Overview of Statistical Analysis

The dataset was imported into Statistical Analysis Software (SAS 9.4) for analysis. Spearman Correlation **(proc corr)** statements were used to measure the magnitude and direction of association between broadband and the social determinants of health (i.g. access to health insurance, median household income) by themselves, and then health outcomes (COVID DR, COVID CFR, and IMR). Spearman Correlations also assessed for multicollinearity across variables, which was corroborated by variance inflation factor (VIF) values, run alongside regression models. Hypothesis testing **(proc ttest)**, namely two-sample-t-tests examined the relationship between dichotomized predictors and the health outcomes of interest. Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-von Mises, and Anderson-Darling tests for normality **(proc univariate)** were utilized to identify non-normal health outcomes. P-values < 0.05 indicate non-normality. This was further corroborated by histograms and Q-Q plots of the residuals. If non-normality was determined, then Poisson Regression **(proc genmod)** was used to quantify the relationship between the predictor variables and health outcomes. Emphasis was placed on the p-values (< 0.20) of the models and the beta coefficients to determine the power of the models and whether broadband was synergistic/ "protective" (negative slope) or antagonistic/ "harmful" (positive slope).

2.3.1 Test for Normality

An amalgamation of tests for normality were utilized: Q-Q plots, Histograms, Shapiro-Wilk, Kolmogorov-Smirnov, Cramer-von Mises, and Anderson-Darling tests. If non-normality of the three health outcomes was present, then Poisson Regression Modeling would be conducted.

2.3.2 Two-Sample-T-Tests to Assess Differences in Health Outcomes by Dichotomized Predictors

According to subject matter expert: Scott D. Woods, Manager of BroadbandUSA, an unofficial estimate for low broadband is < 70% for a community, census block, or county. Therefore low vs. high broadband was categorized as < 70% vs. > 70%. In terms of low-income, <$50k median household income was utilized as the cut-off due to its prior usage in the Georgia broadband study, as directed by Mr. Michael Burns, Director of C2P2 (Ravichandran, 2020). This threshold was explicitly selected after an extensive review of federal government papers and supporting literature, due to its upper limit of the Federal Poverty Level; individuals making above this limit are classified as ineligible for governmental financial assistance (Lu & Eibner, 2017). For similar reasons, the threshold for poverty rate was 20% (Benzow & Fikri, 2020). Due to the already dichotomous nature of county type, this variable remained rural vs. urban county, coded as 0 and 1 respectively. For uninsured population, because the target population is communities in the United States, 10% was the cutoff for high uninsured communities, because it is indicative of the nationwide situation. Predominantly minority communities were aptly classified as > 50% minority percentage. For the PIACC variables, dichotomous cutoffs for literacy and numeracy scores were the nationwide averages of 264 and 249, respectively. Likewise, the nationwide average of 12% was utilized for the cutoff for % receiving SNAP. Due to the dynamic nature of unemployment rate in the United States, particularly during the COVID-19 pandemic, the nationwide average from the PIACC csv file of 5% was used as the threshold for % unemployed. The PIACC nationwide average of 4.2% was also used as the threshold for % Foreign Born. Full breakdown of dichotomized predictors is shown in Table 6.

Table 3: Dummy Variable Assignments for Two-Sample-T-Test Analysis

Dichotomous Coding for Hypothesis Testing

Variable	*0*	*1*
Broadband Access	<70%	>70%
Median Household Income	<50k	>50k
Poverty Rate	<20%	>20%
County Type	Rural	Urban
Uninsured %	<10%	>10%
Minority %	<50%	>50%
Average Literacy Score	<264	>264
Average Numeracy Score	<249	>249
% Receiving SNAP	<12%	>12%
% Foreign Born	<4.2%	>4.2%
% Unemployed	<5%	>5%

2.3.3 Assessing for Multicollinearity

Prior to generating multiple linear regression (MLR) models, Spearman Correlations were utilized to determine the degree to which the predictors were related to one another. If the resulting correlation value > 0.75, then the predictor was deemed "suspicious" and further explored via virulence inflation factor (VIF). If the resulting VIF is greater than 10, then multicollinearity is present and the consequent predictor is deemed unnecessary and should not be included in the MLR model.

2.3.4 Identifying Confounders

First, a simple linear regression (SLR) model was run for COVID DR, CFR, and IMR individually with broadband as the predictor. The beta coefficient for broadband was noted. Each of the other predictor variables were added to the SLR individually and the % change of the beta coefficient for broadband was assessed. If the % change was greater than 10%, then that variable was considered to be a confounder.

2.3.5 Identifying Effect Modifiers

Potential effect modifiers were identified "*a priori*." They were run in a multivariate regression model with broadband as the main predictor in order to assess the p-value. If the p-value of the interaction term was < 0.20, then the predictor was deemed an effect modifier and subsequently included in the full multiple linear regression model to be further filtered for a parsimonious, "best fit" model.

2.4 Choosing Best-Fit Parsimonious Model to Quantify Broadband, SDOH, and COVID-19 Outcomes

After testing for confounding and assessing for effect modification, forward selection technique (**selection method = forward**) was utilized to determine the best fit model. Rather than simply choosing the full model, the appropriate model contained the effect modifiers as main effects in the model and ensured validity via p-values.

3. Results

3.1 Demographic Table

Table 4: Breakdown of Demographic Info by OCR-TA Designated vs. Other Communities

Variable	OCR-TA Communities (N = 41)	Non-Designated-Communities (N = 82)
County Type		
Rural	32 (78.05%)	56 (68.29%)
Urban	9 (21.95%)	26 (31.71%)
Economic Indicators		
Med. Household Inc., Mean ± STD	43915.95 ± 8578.58	48501.78 ± 14535.09
Poverty Rate, Mean ± STD	18.16 ± 4.65	16.36 ± 5.57
% Unemployed, Mean ± STD	5.11 ± 1.45	4.88 ± 1.65
% Receiving SNAP Aid, Mean ± STD	18.30 ± 6.41	15.93 ± 5.67
Connectivity		
Broadband Access %, Mean ± STD	80.36 ± 17.58	77.79 ± 21.63
Skills		
Literacy Score, Mean ± STD	254.53 ± 10.64	257.62 ± 12.29
Numeracy Score, Mean ± STD	238.71 ± 13.01	242.22 ± 14.59
Demographics		
% Minority, Mean ± STD	13.49 ±16.93	15.68 ± 15.87
% Foreign Born, Mean ± STD	4.68 ± 7.00	3.90 ± 5.00

3.2 Results of Tests for Normality

The Q-Q plots for all three health outcomes were non-linear and thus, non-normal, and the histograms for COVID DR and CFR were not uniformly distributed and skewed to the right. However, it should be noted that the histogram for IMR appears "relatively" uniformly distributed, but the other tests for normality counter this pattern. All statistically significant tests (p-value < 0.20) are in bold. Based on these tests, Poisson Regression was utilized.

Table 5: Test for Normality for COVID DR Using Univariate Procedure

Test	P-value
Shapiro-Wilk	**<0.0001**
Kolmogorov-Smirnov	**<0.0100**
Cramer-von Mises	**<0.0050**
Anderson-Darling	**<0.0050**

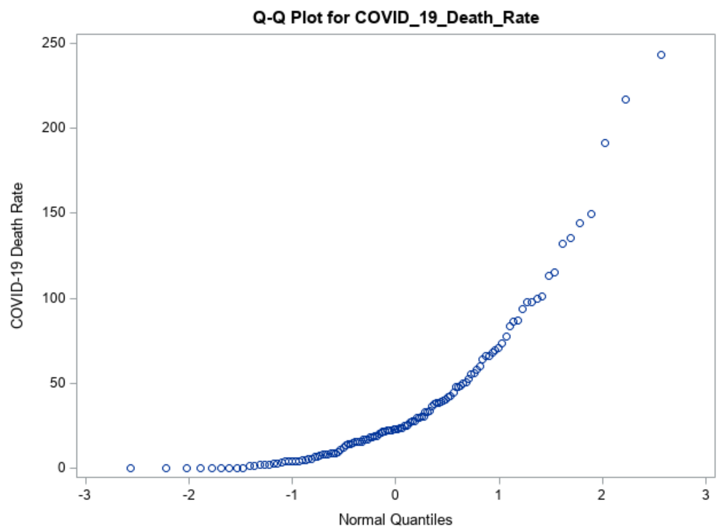

Figure 3: Q-Q Plot for COVID DR

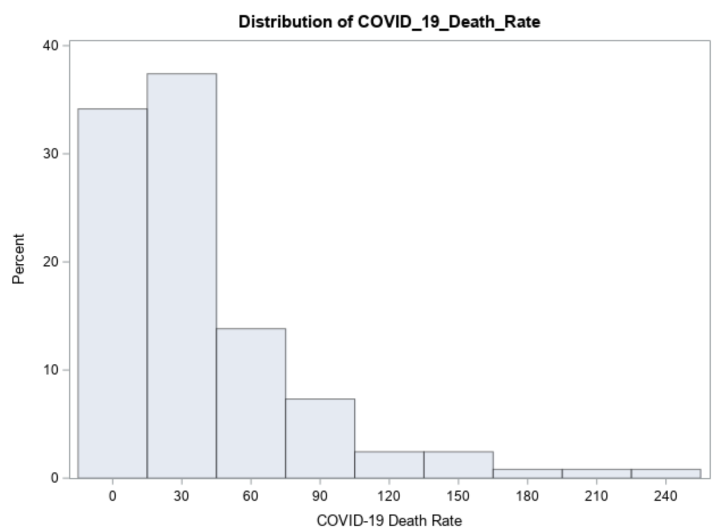

Figure 4: Histogram of COVID DR

Table 6: Test for Normality for COVID-19 CFR Using Univariate Procedure

Test	P-value
Shapiro-Wilk	**<0.0001**
Kolmogorov-Smirnov	**<0.0100**
Cramer-von Mises	**<0.0050**
Anderson-Darling	**<0.0050**

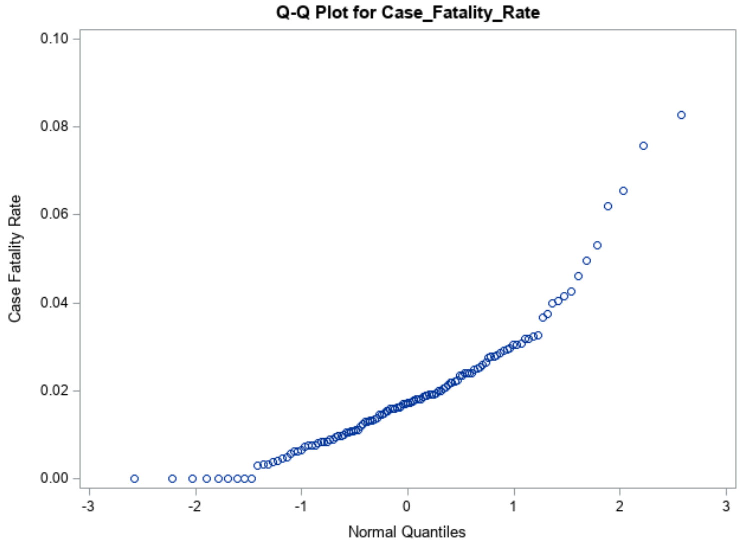

Figure 5: Q-Q Plot for COVID-19 CFR

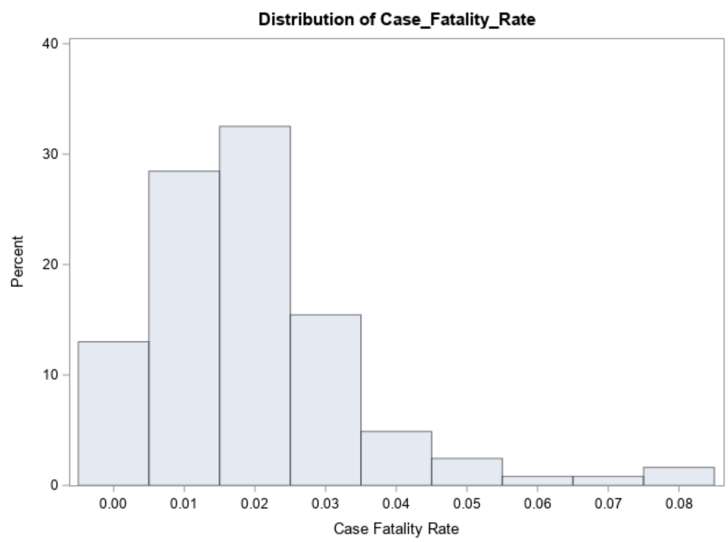

Figure 6: Histogram of COVID-19 CFR

Table 7: Test for Normality for IMR Using Univariate Procedure

Test	**P-value**
Shapiro-Wilk	**0.0001**
Kolmogorov-Smirnov	**<0.0100**
Cramer-von Mises	**<0.0050**
Anderson-Darling	**<0.0050**

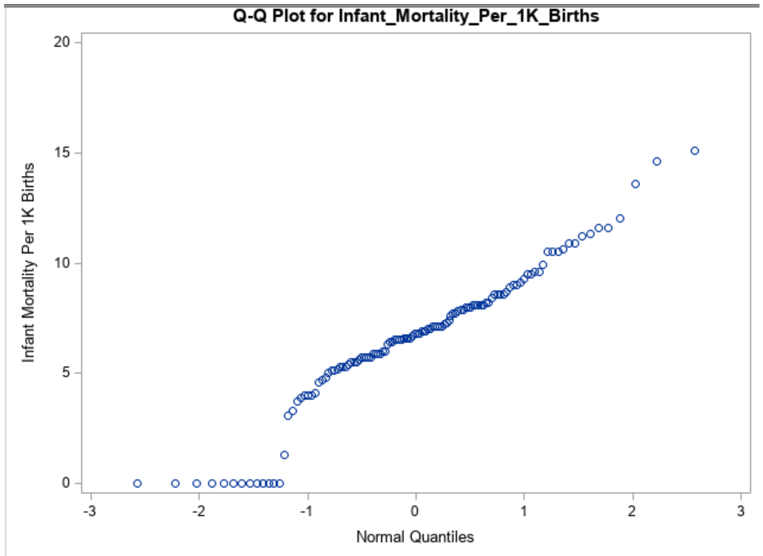

Figure 7: Q-Q Plot for IMR

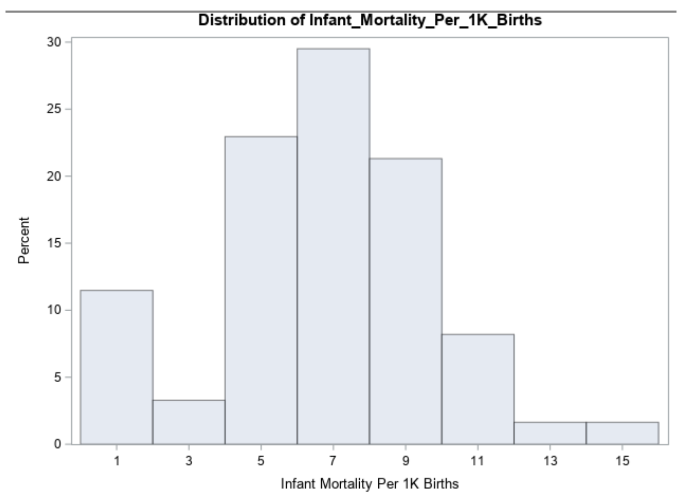

Figure 8: Histogram of IMR

3.3 Spearman Correlation Matrices

Table 8: Spearman Correlation Matrix of Predictors

	Broadband	*Med Inc.*	*Poverty Rate*	*Minority*	*Uninsured*	*County Type*	*EPA Desig.*	*COVID Vuln.*	*Numeracy*	*Literacy*	*SNAP*	*FB*	*Unemployed*
Broadband	1.00	**0.55**	**-0.37**	0.10	**-0.37**	**0.54**	0.01	**-0.23**	**0.46**	**0.46**	**-0.25**	**0.41**	**-0.13**
Med. Inc.	**0.55**	1.00	**-0.79**	0.04	**-0.35**	**0.30**	**-0.13**	**-0.39**	**0.73**	**0.73**	**-0.65**	**0.58**	**-0.35**

Poverty Rate	**0.37**	**-0.79**	1.00	**0.14**	**0.29**	**-0.12**	**0.17**	**0.47**	**-0.77**	**-0.75**	**0.70**	**-0.38**	**0.45**
Minority	0.10	0.043	**0.14**	1.00	**0.16**	0.11	-0.04	**0.32**	**-0.25**	**-0.21**	0.08	**0.38**	**0.31**
Uninsured	**-0.37**	**-0.35**	**0.29**	**0.16**	1.00	**-0.16**	**-0.15**	**0.14**	**-0.46**	**-0.45**	**0.26**	0.10	**0.21**
County Type	**0.54**	**0.30**	**-0.12**	0.11	**-0.16**	1.00	-0.10	-0.03	**0.22**	**0.22**	**-0.28**	**0.21**	-0.05
EPA Desig.	0.01	**-0.13**	**0.17**	-0.04	**-0.15**	-0.10	1.00	**0.16**	-0.10	-0.11	**0.16**	0.08	0.10
COVID Vuln.	**-0.23**	**-0.39**	**0.47**	**0.32**	**0.14**	-0.03	**0.16**	1.00	**-0.48**	**-0.46**	**0.43**	**-0.22**	**0.34**
Numeracy	**0.46**	**0.73**	**-0.77**	**-0.25**	**-0.46**	**0.22**	-0.10	**-0.48**	1.00	**0.99**	**-0.62**	**0.30**	**-0.42**
Literacy	**0.46**	**0.73**	**-0.75**	**-0.21**	**-0.45**	**0.22**	-0.11	**-0.46**	**0.99**	1.00	**-0.62**	**0.30**	**-0.41**
SNAP	**-0.25**	**-0.65**	**0.70**	0.08	**0.26**	**-0.28**	**0.16**	**0.43**	**-0.62**	**-0.62**	1.00	**-0.33**	**0.43**
Foreign Born	**0.41**	**0.58**	**-0.38**	**0.38**	0.10	**0.21**	0.08	**-0.22**	**0.30**	**0.30**	**-0.33**	1.00	**-0.12**
Unemployed	**-0.13**	**-0.35**	**0.45**	**0.31**	**0.21**	-0.05	0.10	**0.34**	**-0.42**	**-0.41**	**0.43**	**0.12**	1.00

Table 9: Spearman Correlation Matrix of Predictors with Outcomes

	COVID-19 DR	COVID-19 CFR	IMR
Broadband	-0.08	0.09	**-0.12**
Med. Household Inc	**-0.14**	0.05	**-0.33**
Poverty Rate	**0.24**	0.05	**0.29**
Minority Presence	**0.52**	**0.35**	0.07
Uninsured Rate	**0.30**	0.01	**0.20**
County Type	**0.12**	0.09	-0.05
EPA Designated	-0.06	-0.03	**0.18**
COVID Vulnerability	**0.42**	**0.15**	**0.18**
Numeracy	**-0.42**	-0.10	**-0.28**
Literacy	**-0.41**	-0.09	**-0.28**
SNAP	**0.13**	0.05	**0.24**
Foreign Born	0.09	0.06	**-0.19**
Unemployed	**0.20**	0.07	**0.18**

3.4 Two-Sample T-Tests

Table 10: Health Disparities by Broadband Access

	Low Broadband (N = 31)	**High Broadband (N = 92)**	**P-value**
COVID-19 Death Rate	**59.75 (39.28 – 80.22)**	**31.19 (23.39 – 39.00)**	**0.0114**
COVID-19 Case Fatality	2.17 (1.57 – 2.77)	1.86 (1.57 – 2.16)	0.3228
Infant Mortality Rate	7.03 (5.70 – 8.36)	6.41 (5.78 – 7.04)	0.3550

Table 11: Health Disparities by Numeracy Rate

	Low Numeracy (N = 92)	**High Numeracy (N = 30)**	**P-value**
COVID-19 Death Rate	**45.64 (35.65 – 55.64)**	**16.87 (10.04 – 23.71)**	**<0.0001**
COVID-19 Case Fatality	2.01 (1.68 – 2.34)	1.72 (1.31 – 2.14)	0.2736
Infant Mortality Rate	**6.8188 (6.1640 – 7.4736)**	**5.8033 (4.5932 – 7.0134)**	**0.1403**

Table 12: Health Disparities by Literacy Rate

	Low Literacy (N = 94)	**High Literacy (N = 28)**	**P-value**
COVID-19 Death Rate	**44.78 (34.93 – 54.63)**	**17.68 (10.46 – 24.90)**	**<0.0001**
COVID-19 Case Fatality	2.01 (1.69 – 2.33)	1.72 (1.28 – 2.17)	0.2989
Infant Mortality Rate	**6.83 (6.19 – 7.47)**	**5.68 (4.40 – 6.97)**	**0.0947**

Table 13: Health Disparities by Minority Presence

	Low Minority (N = 8)	High Minority (N = 115)	P-value
COVID-19 Death Rate	**116.9 (51.12 – 182.7)**	**32.93 (26.33 – 39.53)**	**0.0194**
COVID-19 Case Fatality	**3.11 (1.52 – 4.70)**	**1.86 (1.59 – 2.12)**	**0.0202**
Infant Mortality Rate	**9.63 (7.29 – 11.97)**	**6.35 (5.77 – 6.93)**	**0.0047**

Table 14: Health Disparities by EPA Designated vs. Non-Designated Communities

	TA Communities (N = 41)	Non-TA Communities (N = 82)	P-value
COVID-19 Death Rate	38.77 (23.90 – 53.64)	38.20 (28.66 – 47.74)	0.9474
COVID-19 Case Fatality	1.86 (1.40 – 2.33)	1.98 (1.65 – 2.31)	0.6870
Infant Mortality Rate	**7.48 (6.67 – 8.30)**	**6.11 (5.36 – 6.86)**	**0.0142**

Table 15: Health Disparities by Median Household Income

	Low Median Household Income (N = 89)	High Median Household Income (N = 34)	P-value
COVID-19 Death Rate	38.86 (29.46 – 48.26)	37.16 (21.53 – 52.79)	0.8503
COVID-19 Case Fatality	1.85 (1.53 – 2.17)	2.18 (1.70 – 2.66)	0.2725
Infant Mortality Rate	**7.02 (6.37 – 7.66)**	**5.41 (4.24 – 6.57)**	**0.0199**

Table 16: Health Disparities by Poverty Rate

	High Poverty (N = 28)	Low Poverty (N = 95)	P-value
COVID-19 Death Rate	**49.80 (31.02 – 68.58)**	**35.03 (26.28 – 43.78)**	**0.1232**
COVID-19 Case Fatality	2.05 (1.48 – 2.62)	1.91 (1.60 – 2.21)	0.6528
Infant Mortality Rate	**7.64 (6.34 – 8.94)**	**6.25 (5.62 – 6.89)**	**0.0437**

Table 17: Health Disparities by Population Receiving SNAP Benefits

	Highly SNAP Dependent (N = 103)	Not SNAP Dependent (N = 20)	P-value
COVID-19 Death Rate	**40.40 (31.17 – 49.63)**	**28.03 (16.52 – 39.54)**	**0.0918**
COVID-19 Case Fatality	**2.00 (1.70 – 2.30)**	**1.63 (1.15 – 2.11)**	**0.1916**
Infant Mortality Rate	**6.78 (6.17 – 7.39)**	**5.47 (3.82 – 7.12)**	**0.0929**

Table 18: Health Disparities by Foreign Born Population

	Low Foreign-Born Population (N = 86)	High Foreign-Born Population (N = 36)	P-value
COVID-19 Death Rate	40.42 (29.84 – 50.99)	33.50 (23.85 – 43.15)	0.3346
COVID-19 Case Fatality	**2.03 (1.68 – 2.39)**	**1.71 (1.40 – 2.03)**	**0.1789**
Infant Mortality Rate	**7.06 (6.43 – 7.68)**	**5.40 (4.19 – 6.62)**	**0.0175**

Table 19: Health Disparities by Uninsured Rate

	Low Uninsured Rate (N = 55)	High Uninsured Rate (N = 68)	P-value
COVID-19 Death Rate	**24.46 (16.88 – 32.05)**	**49.66 (37.12 – 62.19)**	**0.0008**
COVID-19 Case Fatality	1.88 (1.46 – 2.30)	1.99 (1.64 – 2.34)	0.6904
Infant Mortality Rate	**6.06 (5.30 – 6.82)**	**6.97 (6.13 – 7.81)**	**0.1110**

Table 20: Health Disparities by Unemployed Rate

	Unemployed > 5% (N = 52)	Unemployed < 5% (N = 71)	P-value
COVID-19 Death Rate	**44.97 (30.86 – 59.09)**	**33.57 (24.33 – 42.81)**	**0.1789**
COVID-19 Case Fatality	1.96 (1.51 – 2.41)	1.92 (1.59 – 2.25)	0.8842
Infant Mortality Rate	6.65 (5.72 – 7.58)	6.51 (5.76 – 7.25)	0.8051

Table 21: Health Disparities by County Type

	Rural (N = 88)	Urban (N = 35)	P-value
COVID-19 Death Rate	36.71 (27.33 – 46.09)	42.61 (27.00 – 58.23)	0.5091
COVID-19 Case Fatality	1.89 (1.56 – 2.21)	2.07 (1.59 – 2.55)	0.5417
Infant Mortality Rate	6.65 (5.91 – 7.39)	6.38 (5.54 – 7.22)	0.6289

3.5 Simple Poisson Regression Models

Table 22: Poisson Simple Regression Models for Health Outcomes*

Outcome	Predictor	Intercept	Beta Coefficient	Wald 95% CI	P-value
COVID-19 Deaths Per 100K Residents	Broadband	4.1683	-0.67	(-0.80, -0.55)	<0.0001
	Med. Household Inc	4.3544	-0.02	(-0.02, -0.01)	<0.0001
	Poverty Rate	2.8216	0.05	(0.04, 0.05)	<0.0001
	Minority	3.0444	0.03	(0.03, 0.03)	<0.0001
	County Type	3.6031	0.15	(0.09, 0.21)	<0.0001
	Vulnerability Score	0.4050	6.17	(5.65, 6.69)	<0.0001
	EPA Designated	3.6429	0.01	(-0.05. 0.08)	0.6336
	Numeracy	12.7369	-0.04	(-0.04, -0.04)	<0.0001
	Literacy	15.1823	-0.05	(-0.05, -0.04)	<0.0001
	SNAP	3.0229	0.04	(0.03, 0.04)	<0.0001
	Foreign Born	3.5860	0.01	(0.01, 0.02)	<0.0001
	Uninsured	3.1873	3.82	(3.22, 4.42)	<0.0001
	Unemployed	2.9576	0.13	(0.12, 0.15)	<0.0001
COVID-19 Case Fatality Rate	Broadband	-4.0212	0.10	(-6.26, 6.46)	0.9755
	Med. Household Inc	-3.7829	-0.003	(-0.11, 0.10)	0.9476
	Poverty Rate	-4.1023	0.009	(-0.23, 0.25)	0.9381
	Minority	-4.1739	0.01	(-0.05, 0.08)	0.6875
	County Type	-3.9697	0.09	(-2.67, 2.85)	0.9479
	Vulnerability Score	-4.7294	1.52	(-19.46, 22.50)	0.8871
	EPA Designated	-3.9321	-0.06	(-2.78, 2.66)	0.9656
	Numeracy	-2.0444	-0.08	(-0.10, 0.08)	0.8644
	Literacy	-1.9368	-0.08	(-0.12, 0.10)	0.8883
	SNAP	-4.0452	0.01	(-0.20, 0.22)	0.9547
	Foreign Born	-3.9269	-0.004	(-0.23, 0.23)	0.9739
	Uninsured	-4.0057	0.54	(-28.69, 29.76)	0.9713
	Unemployed	-4.0952	0.03	(-0.75, 0.81)	0.9389
Infant Mortality Rate Per 1K Live Births	Broadband	1.9574	-0.10	(-0.43, 0.24)	0.5773
	Med. Household Inc	2.5303	-0.01	(-0.02, -0.008)	<0.0001
	Poverty Rate	1.3908	0.03	(0.02, 0.04)	<0.0001
	Minority	1.7885	0.006	(0.002, 0.01)	0.0035
	County Type	1.8941	-0.04	(-0.20, 0.11)	0.5998
	Vulnerability Score	1.0680	1.57	(0.42, 2.72)	0.0073
	EPA Designated	1.8093	0.20	(0.06, 0.35)	0.0051
	Numeracy	4.1577	-0.01	(-0.01, -0.005)	0.0002
	Literacy	4.6158	-0.01	(-0.02, -0.005)	0.0005
	SNAP	1.5424	0.02	(0.009, 0.03)	0.0005
	Foreign Born	1.9659	-0.02	(-0.04, -0.007)	0.0044
	Uninsured	1.8083	0.63	(-0.96, 2.22)	0.4386
	Unemployed	1.5834	0.06	(0.02, 0.10)	0.0049

*Interpretation of Beta coefficient (B): % change in the outcome per unit increase in the predictor

3.6 Best-Fit "Parsimonious" Poisson Models for Health Outcomes

Table 23A: Best Fit Poisson Model for COVID-19 DR

Parameter	Estimate	Standard Error	Wald 95% Confidence Limits		P-value
Intercept	11.95	1.11	9.77	14.12	<.0001
Broadband Access	1.80	0.81	0.21	3.39	0.0263
Median Household Income*	0.05	0.01	0.02	0.08	0.0002
Poverty Rate	-0.04	0.006	-0.06	-0.03	<.0001
County Type	-3.84	0.40	-4.62	-3.05	<.0001
COVID Vulnerability	2.74	0.35	2.06	3.42	<.0001
Minority Presence	0.03	0.002	0.02	0.03	<.0001
% Uninsured	-14.03	1.76	-17.47	-10.58	<.0001
Numeracy Score	0.05	0.02	0.02	0.08	0.0028
Literacy Score	-0.09	0.02	-0.12	-0.05	<.0001
% Foreign Born	0.15	0.02	0.10	0.20	<.0001
% Unemployed	0.31	0.05	0.22	0.40	<.0001
% Receiving SNAP	-0.02	0.004	-0.03	-0.01	<.0001
Broadband*Median Household Income	-0.06	0.015	-0.09	-0.03	<.0001
Broadband*County Type	4.63	0.44	3.77	5.48	<.0001
Broadband*Uninsured	16.05	2.26	11.61	20.48	<.0001
Broadband*Foreign Born	-0.16	0.03	-0.21	-0.10	<.0001
Broadband*Unemployed	-0.44	0.06	-0.56	-0.32	<.0001

*Median Household Income was recoded as Median Household Income / 1000 for standardization purposes.

Table 23B: Similar to Table 23A but with all interaction terms removed

Parameter	Estimate	Standard Error	Wald 95% Confidence Limits		P-value
Intercept	14.74	0.77	13.24	16.25	<0.0001
Broadband Access	-0.14	0.10	-0.33	0.05	0.1422
Median Household Income*	0.001	0.003	-0.005	0.01	0.7854
Poverty Rate	-0.04	0.006	-0.05	-0.03	<0.0001
County Type	0.16	0.04	0.08	0.24	<0.0001
COVID Vulnerability	1.83	0.33	1.19	2.47	<0.0001
Minority Presence	0.02	0.002	0.02	0.03	<0.0001

Parameter	Estimate	Standard Error	Wald 95% Confidence Limits		P-value
% Uninsured	-1.33	0.41	-2.13	-0.54	0.0010
Numeracy Score	0.008	0.01	-0.02	0.04	0.5595
Literacy Score	-0.05	0.01	-0.08	-0.02	0.0004
% Foreign Born	0.003	0.003	-0.003	0.01	0.2778
% Unemployed	-0.04	0.01	-0.06	-0.02	0.0004
% Receiving SNAP	-0.02	0.004	-0.03	-0.01	<0.0001

COVID CFR = N/A (Selection did not retrieve a best-fit model due to lack of fit)

Table 24A: Best Fit Poisson Model for IMR

Parameter	Estimate	Standard Error	Wald 95% Confidence Limits		P-value
Intercept	2.43	0.16	2.13	2.74	<.0001
Median Household Inc*	-0.01	0.003	-0.02	-0.007	<.0001
EPA Designated	0.15	0.07	0.01	0.30	0.0369

*Median Household Income was recoded as Median Household Income / 1000 for standardization purposes.

Table 24B: Best Fit Poisson Model for IMR Without Interaction Terms Being Considered in GENSELECT

Parameter	Estimate	Standard Error	Wald 95% Confidence Limits		P-value
Intercept	2.29	0.17	1.96	2.61	<.0001
Med Household Inc	-0.01	0.003	-0.02	-0.005	0.0003
EPA Designated	0.17	0.07	0.02	0.31	0.0234
Minority	0.005	0.002	0.001	0.009	0.0222

4. Discussion

4.1 Spearman Correlation Interpretations

Contrary to the Georgia Broadband Project, the spearman correlations between broadband and the health outcomes were not strong nor significant. However, when assessing the social determinants of health, we observe a statistically significant (p-value < 0.20) positive correlation between following and COVID DR: poverty rate (ρ = 0.24), minority presence (ρ = 0.52), uninsured rate (ρ = 0.30), COVID vulnerability (ρ = 0.42), county type (ρ = 0.12), and % receiving SNAP (ρ = 0.13). Likewise, a significant negative correlation was observed between COVID DR and the following: median household income (ρ = -0.14), numeracy score (ρ = -0.42), and literacy score (ρ = -0.41). In terms of COVID CFR, there was a statistically significant positive correlation with: minority presence (ρ = 0.35) and COVID vulnerability (ρ = 0.15). There were no significant negative correlations between COVID CFR and any other covariates. For IMR, there was a statistically significant positive correlation with: poverty rate (ρ = 0.29), uninsured rate (ρ = 0.20), EPA Designation (ρ = 0.18), COVID-19 Vulnerability (ρ = 0.18), % receiving SNAP (ρ = 0.24), and unemployed (ρ = 0.18) and a statistically significant negative correlation with: broadband (ρ = -0.12), median household income (ρ = -0.33), numeracy score (ρ = -0.28), literacy score (ρ = -0.28), and % foreign born (ρ = -0.19).

4.2 Two-Sample-T-Test Interpretations

Based on the Two-Sample-Tests, there was no statistical significance observed between OCR TA and non-OCR TA communities (p-value = 0.9474; 0.6870) for the COVID DR and CFR respectively, though the former appears to possess significantly higher IMR (p-value = 0.0142). However, our secondary hypothesis of broadband being protective against the COVID health outcomes holds true based on the combination of the Two-Sample-T-Test (p-value = 0.0114) and the Simple Linear Regression Model (negative beta coefficient) with broadband as the predictor; however, it should be noted that the Two-Sample-T-Test did not portray significance for CFR or IMR (p-value = 0.3228; 0.3550), though the point estimate displayed protection. The Two-Sample-T-Tests for numeracy (p-value < 0.0001), literacy (p-value < 0.0001), poverty rate (p-value = 0.1232), % receiving SNAP (p-value = 0.0918; 0.1916), population uninsured (p-value = 0.0008), and population unemployed (p-value = 0.1789) were statistically significant for at least one of the COVID health outcomes of interest. Additionally, the Two-Sample T-Tests for numeracy (p-value = 0.1403), literacy (p-value = 0.0947), poverty rate (p-value = 0.0437), median household income (p-value = 0.0199), % receiving SNAP (p-value = 0.0929), and population insured (p-value = 0.1110) revealed statistical significance for IMR. Interestingly, minority presence and foreign-born population had a statistically significant opposite effect, where higher minority (p-value = 0.0194; 0.0202; 0.0047) communities actually had a lower burden of the three health outcomes and higher foreign-born communities (p-value = 0.1789; 0.0175) had a lower burden of COVID CFR and IMR, respectively.

4.3 Confounding and Effect Modification Findings and Their Potential Impacts on Policymaking

When assessing for confounding, many of the SDH variables affected the slope of broadband from the simple model by > 10%, indicating that they indeed confounded the relationship between broadband the health outcomes. This highlights the need to improve socioeconomic status via frameworks like Friedman's 5-Tiered Public Health Pyramid, suggesting a multipronged approach is necessary within policy frameworks to combat COVID-19 and infant health outcomes (Frieden, 2010). By reducing poverty, changing the communities' context to make default decisions healthy, implementing long lasting interventions, counseling and educating community members, downstream health benefits could be observed (Frieden, 2010). Such strategies require a qualitative outlook, which is mentioned in the recommendations section of this paper. Furthermore, effect modification was also observed among many of the SDH variables, which suggests stratum-specific effects of SDHs onto the broadband-health outcome pathway. This enables researchers to identify the measures of association between different thresholds within SDH variables, which is valuable for evidence-based policymaking.

4.4 Synergistic vs. Antagonistic Determinants of Health Based on Individual Poisson Models

Due to the non-normality of the health outcome data, Simple and Multiple Poisson Regression were utilized. Simple models for COVID-19 DR exhibited a synergistic, protective relationship with broadband access, median household income, numeracy score, and literacy scores. An antagonist relationship was seen with the other predictors. All but EPA Designation (p-value = 0.6336) did not contain the null value for their respective beta coefficients. In terms of COVID-19 CFR, all of the beta coefficients contained the null (p-values ranged from 0.6875 – 0.9713) so judgements on synergistic vs. antagonistic qualities are not significant. Lastly, for IMR, median household income, urbanity, numeracy score, literacy score, and % foreign born were all synergistic and protective, while poverty rate, minority presence, pandemic vulnerability score, EPA designation, SNAP, and % unemployed were all antagonistic. The rest of the predictors for IMR contained the null, so meaningful extrapolations could not be made. Full breakdown of beta coefficients, their Wald 95% CIs, and their p-values are shown in Table 22. The best-fit "parsimonious" Poisson models were more ambiguous. In fact, for COVID-19 CFR, forward selection did not include any variables apart from the intercept because they do not impose a significant effect to the model if included. As for COVID-19 DR, broadband even appeared "harmful"; however, it should be noted that the p-values for COVID-19 DR's Poisson Model were all statistically significant. When the interaction terms with broadband are removed, however, broadband becomes protective, as was the case in the simple model. One possible explanation for this phenomenon is too many interaction terms in the model, with those interaction terms having extremely high beta coefficients that may cloud the entire model altogether. Furthermore, the limited sample size may have also contributed to the ambiguity of the model. The best fit Poisson model for IMR only included median household income as protective and OCR TA classified communities and minority presence as harmful.

5. Conclusions

5.1 Recommendations

5.1.1 Reduce Broadband Costs via Healthy Market Competition Initiatives

In order to prevent consumers from having to pay monopoly or duopoly broadband costs associated with a lack of providers, subsidizing providers to enhance their services would promote healthier market competition. Localized efforts, such as Comcast's decision to expand broadband coverage to 8000 previously unserved residences and businesses in rural Western Georgia, would cost households <\$10/month for high speed, low latency networks (Comcast, 2020). On a more ambitious scale, broadband infrastructure at the federal level, similar in scale to the Rural Electrification Act (REA) of 1936, is needed. The REA brought electricity to farmland and rural communities; likewise, broadband can be viewed as the 21st century's version of the power grid system of the 1930s, the railroad system of the 1880s, and so forth (National Park Service, 2020) (American Rails).

5.1.2 Promote Smart Growth in Communities Through Broadband Designation Programs

States like Georgia have adopted ordinances (i.e. Achieving Connectivity Everywhere [ACE] Act), that developed a "broadband task force" such as the Georgia Broadband Deployment Initiative (GBDI) responsible for state-wide level remapping, as well as grant programs for governing municipalities (Office of the Governor, 2020). The former allows for more accurate broadband reports that identify high needs communities. The latter permits funding to municipalities, granted they include broadband initiative elements (BIEs) in their local planning proposals (GBDI, 2019). This can give the community broadband ready designation, which is lucrative for businesses, facilities, and technology to invest in the downtown area and spur economic development. Domestic and worldwide trends reveal that economic growth and increased median household income can lead to downstream health benefits and can mitigate a wide array of health outcomes such as COVID-19 mortality and IMR as studied in this paper (Our World in Data, 2016) (BlueCross BlueShield, 2017) (Elgar et al., 2020). Therefore, other states should consider ordinances like ACE to promote smart growth in communities that suffer from the cumulative impacts of decreased broadband and poor health outcomes.

5.2 Next Steps

So far, this assessment of broadband, the social determinants of health, and the three health outcomes of interest had been done for Georgia and here for the nation. There have also been demands to replicate this study or perform variants at the state-level. For example, this work has piqued interest of faculty members at other universities and flagship schools to replicate these methodologies for their respective states by working with local community leaders and organizations to bring in their expertise. However, caution should be taken when interpreting the study findings due to the relatively low sample size. For the sake of this study, only the HP2 and Cool & Connected programs were included with OCR TA N = 42. Future recommendations to the study design include a larger OCR TA sample size (N > 100), by incorporating more OCR TA programs within this study and matching with a higher ratio of controls (i.e., 1:3, 1:4, etc.…). Not only would this achieve a higher overall sample size (N > 500), but this protocol would immensely add to the statistical power of the findings and further validate the Georgia Broadband Study results at the national level.

5.2.1 Qualitative Aspects of Public Health Practice

By working with local leaders, we can also bring in qualitative aspects of public health, one area that this project is lacking. As productive as the tabular reports and significant findings were, there is a need to explore the underlying basis behind "why" a relationship occurs and if there are proxy confounders present. For example, scientific literature and observational studies have proven that people of color experience racial bias in hospitals, longer wait times, and prescribed different treatments, compared to their white counterparts. This is something that should be explored further and the usage of electronic data capturization tools like REDCap. It has been extremely useful in gathering survey data and comments from residents without having to conduct site visits. Not only does this display technological advances that have facilitated scientific projects (i.e. development of the COVID-19 vaccines in record time), but it also enables investigators to gather data from the comforts of their home environment. Likewise, teleconference via secure platforms like Zoom allow for "face-to-face" interactions with community leaders and spur community engagement. Ironically, this requires high-speed, low latency broadband networks, which is the focal point of this research. Furthermore, the use of PhotoVoice, where researchers or citizen science-based groups take photos of notable features of the community to their liking, would corroborate the statistics with first-hand accounts of the situation.

5.2.2 Elevate Broadband Coverage Threshold for Future Quantitative Analyses

Because the FCC had defined broadband coverage as 25 mbps/3 mbps, that was used for this study (Zimmer, 2018). However, as indicated in Table 1, essential tasks like telemedicine and HD videoconferencing require even higher speeds. In fact, the more recent definition of broadband coverage is a large increase from the 2010 definition of 4 mbps/1 mbps and the prior 1996 definition of 200 kbps/kbps. These trends reveal that we are due for more benchmark changes in the near future, especially with rapid advances in technology, "market offerings by broadband providers, and consumer demand" (Zimmer, 2018). Future projects could explore health outcomes at other cutoffs along the ordinal scale (i.e. 100 mbps, 1gig) to see which communities are staying ahead of the curve in preparation for the next benchmark leap and if their health outcomes reflect their preparation. This could allow subsequent spearman correlation assessments, hypothesis tests and simple/Poisson regression models to further capture the broadband divide seen in America.

5.3 Final Takeaways

Across the various statistical methods used in the analysis, there were different statistically significant findings when focusing solely on broadband. The spearman correlations found no significant relationship between broadband access and COVID-19 DR or CFR. However, it was shown to be protective against IMR, as evidenced in Table 9. Alternatively, when stratified dichotomously by low vs. high broadband, broadband deserts were shown to have significantly higher COVID-19 DR, as observed in Table 10. The latter was corroborated by the Simple Poisson model, which indicated a negative beta coefficient attached to broadband, without containing the null value, presented in Table 22. This presents broadband access as an environmental justice concern. Strictly adhering to correlation assessments, Table 9 revealed minority presence was most strongly associated with increased COVID-19 DR and CFR; however, interestingly enough, an opposite effect was seen when dichotomized for the two-sample-t-test in Table 13. Due to the heavy skew in sample size for high minority counties, the power of the hypothesis test is greatly reduced. However, the Simple Poisson model supplemented the significance of minority presence, with Table 22 showcasing a positive slope attached to it for COVID-19 DR and IMR, without containing the null. This propels these health outcomes into the realm of racial justice. Shifting towards educational indicators, numeracy and literacy scores were unique in the sense that they were both protective against all three health outcomes across all formats (correlation matrices, hypothesis testing, poisson modeling). This presents exigence towards exploring other educational variables within the broadband and COVID/IMR directed acyclic graph (DAG). Such variables could include ordinal educational attainment (i.e Less than High School, High School, Bachelor's Degree, Graduate Degree) and may be pulled from the PIACC source where numeracy and literacy score were derived.

Reverting back to the initial hypothesis of whether EPA-Designated OCR TA communities would bear the burden of the health outcomes of interest, although a clear link to COVID-related outcomes cannot be established, there does appear to be higher IMR associated with OCR TA communities. In conjunction with the Georgia Broadband Study, a successful link has been made between broadband access and improved birth outcomes; therefore, future projects should explore this relationship further via the HP2 and Cool & Connected Program. The results from this study suggest that a combination of improved broadband capabilities and exploration of socio-environmental exposures that impact maternal and children's health would be beneficial to the overall health of designated communities.

During the Q&A session of the Georgia Broadband Project, there was tremendous interest in exploring the interaction of social determinants of health within the broadband-health outcome pathway. This projects further emphasizes the need to define such variables that play a crucial role in the burden of health. An extensive literature review would generate such measures in addition to the ones assessed in this study and recommended for further analysis. Additional patterns may impact how we view the social determinants and propel population-based health and action-oriented solutions science into limelight.

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7. Supplemental SAS Programming Material

```
*****************ASSESSING MULTICOLLINEARITY****************;
proc corr data = Analysis spearman;
	var Broadband_Access Median_Household_Income Poverty_Rate Minority__
	Uninsured_Percentage County_Type_n EPA_Designated_n COVID_19_Vulnerability
	Numeracy_Score Literacy_Score SNAP_Std Foreign_Born_Std Unemployed_Std;
Run;
```

Variance Inflation Factor (VIF)

Variable	VIF
Broadband	1.73701
Median Household Income	5.93330
Poverty Rate	4.63489
Minority Percentage	4.13024
Uninsured Percentage	1.63506
County Type (Rural vs. Urban)	1.41246
TA vs. Non-TA Community	1.21485
COVID-19 Vulnerability Index	1.67601
Literacy	198.18165
Numeracy	157.12583
SNAP	2.81260
Foreign Born	2.01579
Unemployed	1.72417

SAS Code to Test for Confounding

Run Simple Models to acquire slope for broadband

```
proc reg data = Analysis;
	model COVID-19 Death Rate = 60.85163-28.55668(Broadband)

Run;
proc reg data = Analysis;
	model COVID-19 CFR= 0.01790 + 0.00190 (Broadband)

Run;
proc reg data = Analysis;
	model Infant Mortality Rate = 7.07011 -0.63644 (Broadband)
```

Run;

Run Simple Models with each confounder added individually to gauge % change in slope for broadband (models w/ % change > 10 in bold)

COVID Death Rate

proc reg data = Analysis;
model COVID-19 Death Rate* = 69.55305-17.44134*(Broadband)* -0.00037136*(Median Household Income)

Run;

proc reg data = Analysis;
model COVID-19 Death Rate* = 17.53694 -11.68334 *(Broadband)* + 1.77150 *(Poverty Rate)

Run;

proc reg data = Analysis;
model COVID-19 Death Rate* = 37.61009 -18.22810*(Broadband)* + 129.49179*(Uninsured)

Run;

proc reg data = Analysis;
model COVID-19 Death Rate* = 24.49110-13.79644*(Broadband)* + 1.65565*(Minority)

Run;

proc reg data = Analysis;
model COVID-19 Death Rate* = 65.94153 -39.66804 *(Broadband)* + 12.82508 *(County Type)

Run;

proc reg data = Analysis;
model COVID-19 Death Rate* = -49.29939-17.53326 *(Broadband)* + 197.12805 *(COVID-19 Vulnerability)

Run;

proc reg data = Analysis;
model COVID-19 Death Rate = 60.55989-28.73871 *(Broadband)* + 1.30472 *(EPA Designation)*

Run;

proc reg data = Analysis;
model COVID-19 Death Rate* = 473.30175 + 13.67120 *(Broadband)* -1.73688 *(Literacy)

Run;

proc reg data = Analysis;

model COVID-19 Death Rate* = 401.98263 + 16.89637 *(Broadband)* -1.56347 *(Numeracy)

Run;

proc reg data = Analysis;

model COVID-19 Death Rate* = 62.29415 -35.37572*(Broadband)* + 0.94246 *(Foreign Born)

Run;

proc reg data = Analysis;

model COVID-19 Death Rate* = 29.87533 -24.77482 *(Broadband)* + 5.64534 *(Unemployed)

Run;

proc reg data = Analysis;

model COVID-19 Death Rate* = 32.31587 -20.34899*(Broadband)* + 1.32076 *(SNAP)

Run;

Case Fatality

proc reg data = Analysis;

model COVID CFR= B_0 + B_1*(Broadband) + B_2*(Possible Confounder);

Run;

Proc reg data = Analysis;

model COVID-19 CFR*= 0.02023+ 0.00488 *(Broadband)* -9.93988E-8 *(Median Household Income)

Run;

proc reg data = Analysis;

model COVID-19 CFR*= 0.01199+ 0.00421*(Broadband)* + 0.00024185 *(Poverty Rate)

Run;

proc reg data = Analysis;

model COVID-19 CFR*= 0.01498 + 0.00320 *(Broadband)* + 0.01625*(Uninsured Percentage)

Run;

proc reg data = Analysis;

model COVID-19 CFR* = 0.01081 + 0.00478 *(Broadband)* + 0.00032283 *(Minority)

Run;

proc reg data = Analysis;
model COVID-19 CFR* = 0.01859 + 0.00038515 *(Broadband)* + 0.00175 *(County Type)

Run;

proc reg data = Analysis;
model COVID-19 CFR*= 0.00080032 + 0.00361*(Broadband)* + 0.03060 *(COVID Vulnerability)

Run;

proc reg data = Analysis;
model COVID-19 CFR= 0.01817+ 0.00207*(Broadband)* -0.00120 *(EPA Designated)*

Run;

proc reg data = Analysis;
model COVID-19 CFR*= 0.06498+ 0.00672*(Broadband)* -0.00019827 *(Literacy)

Run;

proc reg data = Analysis;
model COVID-19 CFR*= 0.06122 + 0.00767*(Broadband)* -0.00019855*(Numeracy)

Run;

proc reg data = Analysis;
model COVID-19 CFR= 0.01775+ 0.00259*(Broadband)* -0.00009552*(Foreign Born)*

Run;

proc reg data = Analysis;
model COVID-19 CFR = 0.01442 + 0.00233*(Broadband)* + 0.00063432 *(Unemployed)*

Run;

proc reg data = Analysis;
model COVID-19 CFR= 0.01490 + 0.00277*(Broadband)* + 0.00013898 *(SNAP)*

Run;

Infant Mortality

proc reg data = Analysis;
***model Infant Mortality Rate* = 9.29949+ 2.22805 (Broadband) -0.00009549 (Median Household Income);**

Run;
proc reg data = Analysis;
***model Infant Mortality Rate* = 1.82812 +1.41588 (Broadband) + 0.213331 (Poverty Rate);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 6.42653-0.34909 (Broadband) + 3.56326 (Uninsured);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 6.14365- 0.25595 (Broadband) + 0.04165 (Minority);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 6.99699-0.47565 (Broadband) + -0.18635(County Type);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 6.74798 -0.82405(Broadband) + 1.39795 (EPA Designated);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 1.51763-0.07087 (Broadband) + 9.91070 (COVID-19 Vulnerability);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 25.60529 + 1.27675(Broadband) -0.07813(Literacy Rate);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 22.42601 + 1.42616(Broadband) -0.07046 (Numeracy Rate);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 6.89542 + 0.21266 (Broadband) -0.11799 (Foreign Born);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 4.82475- 0.35768 (Broadband) + 0.40792 (Unemployed);**

Run;

proc reg data = Analysis;
Model **Infant Mortality = 4.11361+ 0.21965 (Broadband) + 0.13630 (SNAP);**

Run;

Identifying Effect Modifiers

Full Model: COVID Death Rate = B_0 + B_1 (Broadband) + B_2 (Med. Household Inc.)+ B_3 (County Type) B_4 (PVI) + B_5 (Technical Assistance) +…+ B_p (X_p)

Potential Interaction Terms

- Median Household Income
- County Type (Rural vs. Urban)
- Minority Presence
- Uninsured Population
- TA vs. Non-TA Community
- Median Age of Community
- Numeracy Score
- Literacy Score
- Foreign Born
- Unemployed
- SNAP

Define Interaction Terms

```
Data Analysis;
    set Analysis;
    Broad_Income = Broadband_Access*Median_Household_Income;
    Broad_Pov = Broadband_Access*Poverty_Rate;
    Broad_County_Type = Broadband_Access*County_Type_n;
    Broad_Desig = Broadband_Access*EPA_Designated_n;
    Broad_Vulnerability = Broadband_Access*COVID_19_Vulnerability;
    Broad_Minority = Broadband_Access*Minority__;
    Broad_Uninsured = Broadband_Access*Uninsured_Percentage;
    Broad_Numeracy = Broadband_Access*Numeracy_Score;
    Broad_Literacy = Broadband_Access*Literacy_Score;
    Broad_Foreign_Born = Broadband_Access*Foreign_Born;
    Broad_Unemployed = Broadband_Access*Unemployed;
    Broad_SNAP = Broadband_Access*SNAP;

Run;
```

Effect Modification Assessment for COVID-19 Death Rate

Interaction Term	P-value
Broad_Income	**0.0768**
Broad_Pov	**0.1439**
Broad_County_Type	**0.0091**
Broad_Desig	**0.0938**
Broad_Vulnerability	**0.0121**

Broad_Minority	0.5310
Broad_Uninsured	**0.1607**
Broad_Numeracy	**0.0175**
Broad_Literacy	**0.0122**
Broad_Foreign_Born	0.8709
Broad_Unemployed	0.5077
Broad_SNAP	**0.1442**

Effect Modification Assessment for COVID-19 CFR

Interaction Term	P-value
Broad_Income	**0.0130**
Broad_Pov	0.5774
Broad_County_Type	**0.0505**
Broad_Desig	0.5741
Broad_Vulnerability	0.3256
Broad_Minority	0.8607
Broad_Uninsured	0.6244
Broad_Numeracy	**0.1419**
Broad_Literacy	**0.1386**
Broad_Foreign_Born	0.5579
Broad_Unemployed	0.9063
Broad_SNAP	0.7195

Effect Modification Assessment for Infant Mortality Rate

Interaction Term	P-value
Broad_Income	0.9920
Broad_Pov	**0.0015**
Broad_County_Type	0.9148
Broad_Desig	0.4961
Broad_Vulnerability	0.7199
Broad_Minority	0.5331
Broad_Uninsured	**0.0312**
Broad_Numeracy	0.5564
Broad_Literacy	0.4652
Broad_Foreign_Born	0.7809
Broad_Unemployed	0.5966
Broad_SNAP	**0.0843**

Simple Linear Regression Models of Each Predictor Variables Assessed Individually

COVID-19 Death Rate = 60.85163-28.55668 (Broadband)
COVID-19 Death Rate = 61.83006 -0.00049898 (Median Household Income)
COVID-19 Death Rate = 5.60155 + 1.93343 (Poverty Rate)
COVID-19 Death Rate = 13.35021 + 1.67503 (Minority)
COVID-19 Death Rate = 36.71159 + 5.90269 (County Type)
COVID-19 Death Rate = -68.37278 + 207.39058 (Vulnerability Score)
COVID-19 Death Rate = 38.20293 + 0.56488 (EPA Designated)
COVID-19 Death Rate = 390.74324 -1.46172 (Numeracy)
COVID-19 Death Rate = 458.78824 -1.63841(Literacy)
COVID-19 Death Rate = 13.88663 + 1.46577(SNAP)
COVID-19 Death Rate = 35.81117 + 0.62018(Foreign Born)
COVID-19 Death Rate = 19.48341 + 161.95405 (Uninsured Rate)
COVID-19 Death Rate = 9.03761 + 5.91787(Unemployed)

COVID-19 CFR= 0.01790 + 0.00190 (Broadband)
COVID-19 CFR = 0.02239 -6.37059E-8(Median Household Income)
COVID-19 CFR = 0.01628 + 0.00018355(Poverty Rate)
COVID-19 CFR = 0.01467 + 0.00031611(Minority)
COVID-19 CFR = 0.01978 -0.00115 (EPA Designated)
COVID-19 CFR = 0.01888 + 0.00182(County Type)
COVID-19 CFR = 0.00473 + 0.02849 (Vulnerability Score)
COVID-19 CFR = 0.05612 -0.00015233(Numeracy)
COVID-19 CFR = 0.05784 -0.00014984(Literacy)
COVID-19 CFR = 0.01740 + 0.00011926(SNAP)
COVID-19 CFR = 0.01970 -0.00007189 (Foreign Born)
COVID-19 CFR = 0.01816 + 0.01056(Uninsured Rate)
COVID-19 CFR = 0.01638 + 0.00060872(Unemployed)

Infant Mortality Rate = 7.07011 -0.63644 (Broadband)
Infant Mortality Rate = 10.28705 - 0.00007917 (Median Household Income)
Infant Mortality Rate = 3.28177 + 0.19336 (Poverty Rate)
Infant Mortality Rate = 5.93660 + 0.04202 (Minority)
Infant Mortality Rate = 6.10617 + 1.37749 (EPA Designated)
Infant Mortality Rate = 6.64632 -0.26918 (County Type)
Infant Mortality Rate = 1.43986 + 9.95335 (Vulnerability Score)
Infant Mortality Rate = 21.45932 -0.06179 (Numeracy)
Infant Mortality Rate = 24.22715 -0.06884 (Literacy)
Infant Mortality Rate = 4.31305 + 0.13472 (SNAP)
Infant Mortality Rate = 7.05475 -0.11606 (Foreign Born)
Infant Mortality Rate = 6.07748 + 4.19715 (Uninsured Rate)
Infant Mortality Rate = 4.52324+ 0.41194 (Unemployed)

Interpretation of SLR Models

For the SLR models, beta coefficients whose p-values < 0.20 indicate significance and explanatory models. Thus, significant variables are shown in bold. The remaining are not highlighted, though the sign of the beta coefficient indicated the point estimate relationship (synergistic vs. antagonistic); however, the latter is not significant and therefore not explanatory and should be taken with caution. Based on the SLR models for COVID-19 Death Rate, broadband access, median household income, numeracy score, and literacy score were all synergistic due to the statistically significant negative slope attached to their respective beta coefficients. On the other hand, poverty rate, minority presence, vulnerability score, population receiving SNAP benefits, uninsured rate, and unemployed rate were all antagonistic due to their significant positive slopes. For COVID CFR, numeracy and literacy score were synergistic, whereas vulnerability score and minority presence were antagonistic. Lastly for IMR, numeracy score, literacy score, and % foreign born are synergistic, while median household income, poverty rate, minority presence, EPA designation, vulnerability score, population receiving SNAP, and unemployed rate are antagonistic

SAS Code to Select Best-Fit Model

proc hpgenselect data = Analysis;

model COVID-Death Rate = Full Model with Interaction Terms: / selection method = forward ;

Run;

proc hpgenselect data = Analysis;
model COVID CFR = Full Model with Interaction Terms / selection method = forward;

Run;

proc hpgenselect data = Analysis;
model IMR= Full Model with Interaction Terms selection = forward

Run;