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Broadband Access and Health Outcomes in FCC Priority Counties: A Longitudinal Analysis

Abstract

Background: The relationship between broadband access and health outcomes is an emerging field of interest within public health research. In an increasingly digital world, it is important to understand how to best allocate broadband resources to maximize health impact and decrease health disparities. This study specifically investigates how levels of broadband connectivity are associated with health metrics for conditions such as diabetes, obesity, and preventable hospitalizations in counties identified as 'priority' by the Federal Communications Commission (FCC) due to their low broadband access and high rates of chronic disease.

Objective: To understand the longitudinal relationship between broadband access and health outcomes in priority counties, specifically focusing on diabetes, obesity, and preventable hospitalizations.

Methods: This study analyzes data from 171 FCC priority counties from 2013-2020. Using regression models, we explore how broadband metrics, including broadband subscriptions and download speed, along with county characteristics such as rurality and persistent poverty, predict health outcomes. Health outcomes of interest include diabetes prevalence, obesity rates, and preventable hospitalizations.

Results: A 1 percentage point increase in broadband subscriptions was associated with a 0.5% decrease in the odds of diabetes prevalence (odds ratio [OR] 0.995, 95% Confidence Interval [CI] 0.992-0.997). No significant relationship was found between broadband and obesity rates and preventable hospitalizations. County disparities were evident, with counties experiencing persistent poverty showing a 10% increase in the odds of diabetes prevalence (OR 1.100, 95% CI 1.062-1.140) and a 20.3% increase in preventable hospitalizations ($\beta=1.203$, 95% CI 1.131-1.280, $P<.001$). Rural counties were predicted to have a 17.6% increase in the odds of obesity prevalence (OR 1.176, 95% CI 1.127-1.228) and a 15.1% increase in the odds of diabetes prevalence (OR 1.151, 95% CI 1.111-1.191).

Conclusions: Our data suggests that increased access to broadband may be correlated with decreased rates of diabetes in FCC priority counties. The study highlights the variable relationship between broadband access and health outcomes and predicts poorer health outcomes in rural, persistent poverty counties. This analysis provides a baseline for understanding the dynamics between broadband and health in critical need areas. Such insights highlight how expanding broadband infrastructure, especially in rural and impoverished regions where disease burden is high, may help reduce health disparities and improve healthcare service access. Future data can be incorporated to clarify causality and model how the adoption of broadband infrastructure may take time to facilitate telehealth usage and ultimately support improved health outcomes, and how these dynamics may differ depending on county characteristics.

Keywords: Broadband Access; Internet Access, Diabetes; Preventable Hospitalizations; Rural Health; Access to Care

Introduction

Internet access has become a critical component of modern healthcare, influencing patient-provider interactions, care delivery, health maintenance, and education. Both the broadband access and digital literacy required to benefit from and navigate telehealth vary greatly across the United States. Improving broadband and digital literacy are therefore potential targets to promote health equity in today's healthcare landscape.

Direct benefits of telehealth are clear: providers can now remotely meet with patients, monitor chronic conditions, and deliver public health advice and education, ultimately freeing up critical hospital resources for the direst conditions [1]. More broadly, lack of broadband access influences all five social determinants of health domains defined by the American Medical Association (AMA), which in turn affects health outcomes and exacerbates health disparities [2]. Recognizing that quality broadband access is tied to health outcomes, the Federal Communications Commission (FCC) identified critical need counties with below average levels of broadband access and above average rates of chronic diseases [3]. This particular concentration of socio-economic and health challenges in FCC priority counties provides a unique and relevant environment to study the direct

relationship between broadband access and health metrics. By concentrating on these counties, our research aims to provide targeted insights into areas that are not only underserved but also stand to benefit the most from interventions in digital infrastructure.

Though many health outcomes are of interest, chronic conditions, like diabetes and obesity, as well as preventable hospitalizations present as relevant, measurable variables to explore a snapshot of broadband's effect on health. Diabetes and obesity are on the rise in the United States, being among the most prevalent and impactful chronic health conditions. They represent significant public health challenges due to their association with a range of serious complications and high healthcare costs. Both are well documented chronic conditions with robust longitudinal data available. Preventable hospitalizations, which are among the costliest routes of healthcare, not only pose a significant economic burden but also provide a measure of a healthcare system's efficiency, potentially informing where to best deploy resources such as telehealth.

The integration of broadband access and digital literacy into healthcare systems presents a crucial avenue for promoting health equity and ultimately improving health outcomes. Telehealth services (supported by quality broadband and digital literacy) can help mitigate health disparities and promote health equity, especially in rural and low-income areas, offering a promising solution to enhance patient-provider interactions. Telehealth is particularly primed to impact diabetes and obesity, as it can provide a platform for continuous monitoring, patient education, support lifestyle modifications, and reducing preventable hospitalizations. Our longitudinal analysis highlights the importance of high quality broadband access and the resulting positive health outcomes.

The aim of this study is to examine the longitudinal relationship between broadband access and key health outcomes, specifically diabetes, obesity, and preventable hospitalizations, in FCC priority counties. We hypothesize that increased broadband access is associated with improved health outcomes, particularly in the management of chronic conditions like diabetes and obesity, and that disparities in health outcomes may vary based on county characteristics such as rurality and persistent poverty.

Prior Work

With growing telehealth usage, many argue that high quality broadband access is a crucial social determinant of health [2]. This viewpoint was supported by the Centers for Disease Control (CDC), who highlighted that telehealth and high quality broadband could improve many aspects of health, including but not limited to access to care and risk of transmission of COVID-19 [1].

Broadband has many potentially positive impacts on health. Reporting on a cross-section of national data from 2015, the FCC found that counties in higher quintiles of broadband access had on average 9.6% lower diabetes prevalence relative to lower quintiles [4]. Research also suggests that telehealth leads to higher engagement and self-efficacy for diabetes patients, and appears more effective at improving outcomes for type II diabetes patients relative to conventional care [5], [35]. A meta-analysis found that telehealth led to between 5-11% reduction in all-cause and condition-related hospitalizations [6].

Although diabetes and obesity are tightly correlated, broadband and obesity present a relationship that much of the current body of research is conflicted on, showing positive relationships, no relationships, and negative relationships [7], [8]. However, much of the literature focuses on the relationship between hours spent on the internet and health. This metric of screen time's effect on obesity is different from broadband access on obesity—our study focuses on the latter. Research which considers broadband access rather than overuse is lacking. One article emphasizes the idea

that uninsured and minority groups are disproportionately affected by obesity and calls for digital health interventions [9]. This brings attention to the idea that broadband access could be beneficial in decreasing this health disparity. We hypothesize that broadband access can impact obesity through multiple mechanisms, including providing access to online health resources, facilitating telehealth services, supporting digital behavioral interventions, enabling online community support, and influencing broad social determinants of health like education and employment.

Additionally, there is a gap in research which examines broadband and health outcomes longitudinally. One of the few longitudinal analyses includes a 2023 study, which found that health outcomes for common procedures in Medicare improved by 5% after broadband internet roll out across ZIP codes from 1999 to 2009 [10]. This study highlighted how broadband access helped patients choose higher-quality providers, with some evidence that broadband also improved the overall provider quality [10].

While previous studies have investigated relationships between broadband and health outcomes, many of these studies are cross-sectional in nature and focus on internet-use (and abuse) and health outcomes [4], [7], [8]. Our work takes a more focused approach, exploring the relationship between broadband access and specific health outcomes over time in FCC critical need counties. The FCC priority list serves as a guide to investigate 1) characteristics of areas most needing support and 2) variance in the relationship between broadband and health outcomes in such areas [11]. This investigation may set the stage for future work that examines causal relationships and mechanisms underlying these observations.

Methods

Three individual regression models were fit to predict diabetes rates, obesity rates, and preventable hospitalizations in 171 priority counties from 2013-2020 using publicly available health outcomes data, census broadband data, and FCC priority county data. All data have been aligned by County FIPS (Federal Information Processing Standard Publication) codes and analyzed at the United States county level.

Population

The FCC defined priority counties as those with a population over 25,000, where less than 50% of households have broadband access, less than 60% of households have adopted internet, over 10% of the population has diabetes, and over 28% of the population has obesity [3]. Of the 214 FCC priority counties, 171 were included in the longitudinal analysis after screening for availability of historical data and excluding outliers (see supplemental for outlier exclusion criteria).

Covariates

The FCC demographic data included binary variables indicating: if a county is rural, experiences persistent poverty, there is a shortage of Primary Care Physicians, and there is a high percentage of veterans, Alaskan Natives / American Indians, or persons over 65 years old compared to national averages [3].

Broadband Variables

Because weak broadband connections are insufficient to support telehealth services, broadband access and quality were quantified via three variables: 1) a ratio of the county median download speed to the national maximum download speed, which represents the quality of broadband infrastructure within a county compared to national maximum. Higher ratios suggest better quality

infrastructure, which is crucial for supporting robust telehealth services. 2) the percent of households with subscriptions at advanced speeds (>25 Mbps). This variable measures the availability of relatively high-speed internet in households, aligning with FCC standards for adequate broadband speeds necessary for modern applications, including telehealth. This is a direct measure of service quality. Lastly, 3) the percent of households with broadband subscriptions, which captures penetration or uptake of broadband among the population, reflecting both the accessibility of broadband services and readiness of the population to adopt digital technologies. The broadband metrics were chosen for two primary reasons. First, as discussed above, they capture both broadband access and quality, allowing for a clearer distinction of which aspects of broadband are most strongly linked to health outcomes. Second, these metrics correspond to the three components of the Internet Access Score (IAI Score), a widely used measure in research and policymaking for assessing digital connectivity. By utilizing metrics such as ratios, measures are standardized and more comparable across different contexts.

The broadband variables are reported over time periods rather than single points in time due to the nature of the dataset they were extracted from (5-year American Community Survey data); the time period level data are less likely to reflect fluctuations over time but provide reliable reports of areas with small populations [12], [13], [14]. Broadband access variables were measured independently rather than combining them into a single latent variable, allowing for a more granular analysis of how different aspects of broadband access impact health outcomes. Separating these variables enables assessment of both quality of broadband alongside general availability and its impact on health. All data used in this analysis was analyzed at the county level; data from FCC Form 477 (percentage of households with download speeds greater than 25 Mbps and the download speed ratio) were aggregated to the county level from census FIPS blocks while the census data on percentage of households with a broadband subscription was already aggregated at the county level [15], [3], [4]. Detailed variable descriptions and further notes are described in the supplement.

Health Variables

Diabetes and Obesity

Diabetes and obesity prevalences were collected as part of the CDC's United States Diabetes Surveillance System and measured as the age-adjusted percentage of adults aged 20+ in a county with diabetes or obesity, respectively [16].

Preventable Hospitalizations

Preventable hospitalizations were measured by population based, age and sex adjusted prevention quality indicators (PQI) per 1,000 Medicare beneficiaries aged 18+. PQI uses hospital discharges to identify admissions that could have been avoided through access to high quality outpatient care and aims to capture cases of potentially preventable complications [17], [18].

Data Alignment

The health variables were available yearly at a county level and aligned with the broadband data by county FIPS code. As the broadband subscription variable was collected over a five year period, while the health data and broadband speed variables are annual statistics, the data was aligned by considering the final year of data relevant to the broadband time period and merging by this year – as an example, health data from 2017 was aligned with broadband data spanning 2013-2017.

Data Exclusion

From the 214 FCC priority counties, 27 were excluded due to missing data for some time periods. Two general classes of outliers were identified: (1) counties with very high numbers of preventable hospitalizations that decreased dramatically over time and (2) counties with unusual trends in broadband variables over time, such as a dramatic drop in speeds (e.g., from 25 Mbps to 2 Mbps in one time period). To account for external factors that might explain substantial reductions in hospitalizations—such as changes in hospital policies—an indicator variable, termed “dynamic hospitalizations,” was created. This variable identifies counties where hospitalizations decreased by at least half between consecutive time periods. Rather than excluding these counties as outliers, they were included in the analysis, and this variable was added to the regression equation to better understand health outcomes in counties that experienced these changes. Any counties in which speeds decreased by at least half between consecutive time periods were excluded from analysis; on average, speeds were seen to increase over time (Table 2). Though decreasing speeds are possible, the authors believed decreasing speeds at this rate were likely data errors. To view more detailed outlier screening methods, please consult the supplement. In total, 16 counties were excluded from analysis as outliers, resulting in a 171-county sample. Models were then refitted on the data excluding these outliers.

To better understand outlier influence, we also performed a sensitivity analysis in which regression models were refit on all data, the results of which are addressed in the discussion and metrics are available in the supplement (Table S1A-C).

Regression Analysis

A Pearson’s correlation matrix was generated to initially explore linear correlations between the continuous variables of interest, using county averages over the four periods of collected data (Figure 1). A comparison of Pearson’s correlations to Simpson’s and a pre-and-post outlier exclusion comparison supported similar trends and is detailed in the supplement (Figure S1A-D).

Three repeated measure regression models with fixed effects for time were fit to predict the three health variables (diabetes, obesity, and preventable hospitalizations) and explore health disparities across county subgroups over time. Beta regression models with a logit link function were selected to predict the two percentage outcomes, diabetes and obesity, as they are specifically designed for bounded outcomes like percentages. These models address challenges such as multicollinearity, heteroskedasticity, and skewness, which might otherwise compromise the validity of results. For preventable hospitalizations, a negative binomial regression was applied, as it is well-suited for count data with overdispersion. To avoid overfitting and balance model complexity with fit, feature selection was conducted prior to model training in R using the `regsubsets()` function. This function performs an exhaustive search, systematically evaluating all possible combinations of demographic covariates from the FCC dataset and broadband variables. For each subset, various fit metrics, such as Adjusted R^2 and Schwartz’s Information Criterion (Bayesian Information Criterion, BIC), were generated and made available for evaluation. The final selection of predictor variables, including their number and composition, was determined based on these metrics (please see the supplement for further details on the feature selection process). The independent and dependent variables included in the three models are as follows:

Diabetes Prevalence ~ Percent Broadband Subscriptions + Download Speed + Veteran + Persistent Poverty + Rural + Dynamic Hospitalizations + Time Period

Obesity Prevalence ~ Download Speed + Veteran + Persistent Poverty + Rural + Dynamic Hospitalizations + Time Period

Robust standard errors were computed to account for the repeated measures design, heteroskedasticity and potential correlations of data clustered into subgroups. The corresponding confidence intervals were exponentiated and reported.

Ethical Considerations

Our work uses publicly available data related to broadband access and health outcomes. The data were fully anonymized and aggregated at the county level and therefore do not contain any personally identifiable information. Therefore, ethical review and approval were not required per federal regulations and their use does not require ethics board review or approval.

Results

Many of the 171 priority counties are rural and a majority have a high veteran population compared to national averages, with a smaller number of counties having a primary care physician shortage or experiencing persistent poverty (Table 1).

Over the 4-year period and averaged across the 171 priority counties, preventable hospitalizations decreased considerably, obesity prevalence increased very slightly (and the standard deviation in obesity between counties increased), and diabetes prevalence remained similar (Table 2). Additionally, download speed increased (and standard deviation between counties increased), percentage subscriptions increased, and percentage households increased.

Table 1. Demographics characteristics of FCC 2017 priority counties (N=171).

County Characteristic	Counties, n (%)
Rural ^a	135 (78.9)
PCP Shortage ^b	51 (29.8)
Persistent Poverty ^c	44 (25.7)
Veteran ^d	122 (71.3)

^a per FCC: rural counties have a majority population in rural areas and total population equal or exceeding the median population for rural counties (i.e., $\geq 15,000$). For rural counties, health inclusion thresholds were normalized to rural metrics [3].

^b PCP (primary care physician), shortage per Health Resources and Services Administration thresholds [3].

^c Persistent Poverty: defined by the census as

“geographies are typically considered to be in persistent poverty if they maintained poverty rates of 20% or more for 30 years.” [\[17\]](#)

^d population percentages are above or below the national average percentage of veterans [\[3\]](#).

Table 2. Trends in preventable hospitalizations, obesity, diabetes, and broadband access in FCC priority counties from 2013- 2020.

	Preventable Hospitalizations, count (SD)	Obesity Prevalence, mean (SD)	Diabetes Prevalence, mean (SD)	Download Speed (Mbps), mean (SD)	Percent Subscriptions, mean (SD)	Percent Advanced Speed, mean (SD)
Time Period						
2013-2017	58.8 (18.5)	29.4 (4.8)	9.9 (2.1)	10.6 (4.3)	61.9 (7.3)	36.9 (6.0)
2014-2018	55.7 (17.6)	30.1 (5.2)	10.1 (2.1)	16.3 (6.6)	65.1 (7.5)	46.9 (5.4)
2015-2019	32.8 (11.1)	30.4 (4.9)	10.0 (1.8)	15.6 (6.6)	68.4 (7.5)	47.3 (5.1)
2016-2020	23.9 (7.9)	30.3 (5.8)	9.9 (1.9)	19.3 (6.1)	72.8 (7.3)	50.2 (5.0)

The Pearson’s correlation matrix (Figure 1) suggests a negative linear relationship between percent subscriptions and all of the health outcome variables. Percent obesity and percent diabetes are highly positively correlated with each other. A sensitivity analysis considering Spearman correlations and the effect of including outlying data points on these correlations show similar strength and direction in correlations, suggesting consistent, linear and monotonic relationships (Figure S1A-D).

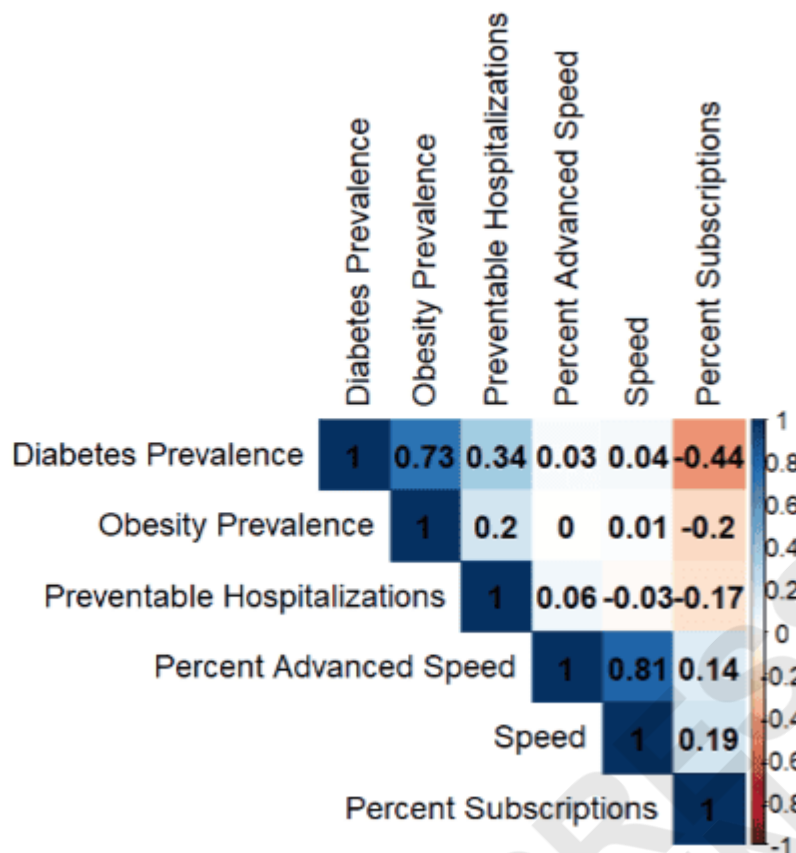


Figure 1. The Pearson's correlation matrix

The Pearson's correlation matrix explores linear relationships between continuous variables, using averages across all 171 FCC priority counties and over time periods (2013-2020).

Regression Results

Overall, the models predict negative relationships between diabetes and broadband subscriptions. No relationship was found between broadband and obesity and broadband and preventable hospitalizations. Subgroup membership (i.e. being a county with persistent poverty) had a highly significant effect on predicting health outcomes, providing a view of factors that may contribute to health inequity in priority counties.

Regression coefficients were computed as log-odds for the beta-regression models; odds ratios and 95% confidence intervals were calculated with robust standard errors, exponentiated, and reported as percentage increases or decreases in odds of the outcomes. For the negative binomial model, coefficients represent the log of expected counts; coefficients and 95% confidence intervals were computed with robust standard errors, exponentiated, and reported as percentage increases or decreases in the number of preventable hospitalizations.

For every 1 percentage point increase in broadband subscriptions, the model predicts that the average odds of diabetes prevalence will decrease by 0.5% (OR 0.995, 95% CI 0.992-0.997), holding all other variables constant and controlling for time (Table 3A). For every 1 Mbps increase in download speed, the model predicts that the odds of diabetes prevalence will increase by 0.3%, (OR 1.003, 95% CI 1.000-1.005) holding all other variables constant and controlling for time. For counties with a high veteran population, there is an estimated average 5.1% (OR 0.949, 95% CI 0.915-0.984) decrease in odds of diabetes prevalence compared to counties with a low veteran population. Counties with persistent poverty are predicted on average to have 10% (OR 1.100, 95% CI 1.062-1.140) higher odds of diabetes prevalence compared to counties that do not

experience persistent poverty. Rural counties had an estimated average 15.1% (OR 1.151, 95% CI 1.112-1.191) higher odds of diabetes prevalence compared to urban counties. The effect of time was not found to be significant.

The model does not find speed to have a significant effect on obesity prevalence, (OR 1.001, 95% CI 0.998-1.004) (Table 3B). Counties with a high veteran population have an estimated average decrease of 8.1% in the odds of obesity prevalence compared to counties with a low veteran population (OR 0.919, 95% CI 0.881-0.958). The model does not find persistent poverty to have a significant effect on obesity prevalence (OR 1.037, 95% CI 0.993-1.083). The average odds of obesity prevalence in rural counties is estimated to be 17.6% (OR 1.176, 95% CI 1.127-1.228) greater than in nonrural counties. The effect of time was not found to be significant.

The model does not find percent broadband subscriptions to have a significant effect on the number of preventable hospitalizations (standardized β coefficient=0.999, 95% CI 0.995-1.003, $P=.6$), holding other variables constant (Table 3C). The model does not find primary care physician shortage (PCPS) to have a significant effect on the number of preventable hospitalizations (standardized β coefficient=1.041, 95% CI 0.998-1.087, $P=.06$). Controlling for all other variables, counties with persistent poverty are on average predicted to have 20.3% more preventable hospitalizations than counties that do not have persistent poverty, (standardized β coefficient=1.203, 95% CI 1.131-1.280, $P<.001$). The effect of time between 2014-2018 on preventable hospitalizations was not found to be significant (standardized β coefficient=0.949, 95% CI 0.891-1.012, $P=.11$), but between 2015-2019 the effect of year became significant, such that the model predicts 43.8% (standardized β coefficient=0.562, 95% CI 0.524-0.603, $P<.001$) fewer preventable hospitalizations compared to 2013-2017, and 58.9% (standardized β coefficient=0.411, 95% CI 0.379-0.446, $P<.001$) fewer preventable hospitalizations between 2016-2020 compared to 2013-2017, holding all other variables constant.

Table 3. Regression analyses of relationships between broadband and health outcomes over time (2013-2020) in FCC priority counties (N=171), controlling for county-level characteristics.

A. Diabetes Prevalence Beta Regression	Variable	OR ^a (95% CI)
	Intercept	0.132 (0.118-0.156) ***
	Percent Subscriptions	0.995 (0.992-0.997) ***
	Download Speed	1.003 (1.000-1.005) *
	Veteran	0.949 (0.915-0.984) **
	Persistent Poverty	1.100 (1.062-1.140) ***
	Rural	1.151 (1.112-1.191) ***
	Dynamic Hospitalizations	0.964 (0.927-1.001)
	2014-2018	1.026 (0.983-1.071)
	2015-2019	1.033 (0.989-1.078)
	2016-2020	1.037 (0.986-1.091)

B. Obesity Prevalence Beta Regression				
	Intercept	0.382 (0.358-0.407) ***		
	Download Speed	1.001 (0.998-1.004)		
	Veteran	0.919 (0.881-0.958) ***		
	Persistent Poverty	1.037 (0.993-1.083)		
	Rural	1.176 (1.127-1.228) ***		
	Dynamic Hospitalizations	0.982 (0.936-1.030)		
	2014-2018	1.029 (0.977-1.084)		
	2015-2019	1.048 (0.998-1.100)		
	2016-2020	1.035 (0.977-1.096)		
C. Preventable Hospitalizations Negative Binomial Regression				
		β Coefficient (95% CI)	P Value	Z Score
	Intercept	59.175 (46.430-75.420)	<.001	33.0
	Percent Subscriptions	0.999 (0.995-1.003)	.60	-0.53
	PCPS	1.041 (0.998-1.087)	.06	1.8
	Persistent Poverty	1.203 (1.131-1.280)	<.001	5.9
	Dynamic Hospitalizations	0.969 (0.917-1.023)	.25	-1.6
	2014-2018	0.949 (0.891-1.012)	.11	-16.0
	2015-2019	0.562 (0.524-0.603)	<.001	-21.5
	2016-2020	0.411 (0.379-0.446)	<.001	-1.1

OR = odds ratio, *, **, *** denotes variables were found to be significant at the $P < .05$, $P < .01$, $P < .001$ levels, respectively.

Discussion

Principal Results

The findings highlight how county characteristics contribute highly to variance in health outcomes – notably, counties with a high veteran population appear to have better health outcomes, while rural and persistent poverty counties appear to have worse health outcomes. Controlling for differences between groups, percentage diabetes was seen to have a slight negative relationship with broadband subscriptions, while obesity and preventable hospitalizations were not found to be related to broadband. This suggests that while broadband access may play a role in shaping certain health outcomes, it is only one of many contributing factors, including socio-economic conditions, healthcare access, and community characteristics.

Although the dataset spans a six-year period, it is possible that there is a lag between the increased broadband speed and subscriptions and their subsequent impact on health outcomes.

This temporal delay could obscure immediate correlations within the dataset. Therefore, incorporating more recent data points into a time series analysis could better model this relationship and help elucidate any delayed impacts on health outcomes. Considering the exploratory boxplots in Figure S2A-F, health outcomes contrast with broadband access, such that counties with high veteran populations appear to have better broadband and counties that are rural and persistent poverty have proportionally fewer broadband subscriptions than other groups. These results suggest a potential interaction effect, and an analysis with future data could incorporate interactions between county subgroups and broadband variables to predict how early metrics of broadband might predict health outcomes years later in counties with these specific characteristics.

Diabetes Negative Relationship with Broadband

The regression models suggest that every 1 percentage point increase in broadband subscriptions is associated with a 0.5% decrease in the odds of diabetes prevalence, controlling for time, persistent poverty, rurality, and veteran status. Though the effect is small, other studies have found similar trends; reporting on a cross-section of national data from 2015, the FCC found that counties in higher quintiles of broadband access had on average 9.6% lower diabetes prevalence relative to lower quintiles [4]. Diabetes may be a particularly well-suited condition for management via telehealth, as care benefits from preventing diabetic related complications via health-coaching with a physician [5], [20], [21]. Research also suggests that telehealth leads to higher engagement and self-efficacy for diabetes patients, and appears more effective at improving outcomes in patients with type II diabetes relative to conventional care [5]. Such findings support the idea that increasing broadband access may be particularly effective in diabetes care.

The confidence interval for the slight positive relationship between speed and diabetes rates nearly includes one, suggesting that this relationship may not be accurate for population level inferences; the observed relationship may reflect a threshold of benefit, such that having broadband past a certain speed no longer offers improved access to health resources, and households with very high broadband speeds may experience negative consequences of internet overuse.

Obesity and Preventable Hospitalizations and No Relationship with Broadband

No significant relationship was found between broadband subscriptions and preventable hospitalizations when controlling for year, county subgroups, and fluctuating dynamics in preventable hospitalizations. Future research that explores the role of digital literacy in reducing hospitalizations may help clarify this relationship, as broadband access alone may not be adequate, and ideally communities are supported with both access and education. It is also possible that increased broadband subscriptions and internet speeds may take longer to impact preventable hospitalizations. Considering early broadband metrics with more recent health outcomes may better clarify this relationship. Finding methods to reduce preventable hospitalizations is particularly important, as inpatient care is a primary driver of medical costs and resources [22].

Although diabetes and obesity are tightly correlated, no significant correlation between broadband variables and obesity percentages was found. There may be external factors that complicate the relationship between obesity and broadband that are not present for diabetes. Obesity is a vastly undertreated disease; although over 40% of the U.S population is obese, less than 1% receive treatment [23], [24]. The social stigma surrounding obesity results in patients avoiding discussions with their physicians around losing weight, and many patients infrequently connect weight with

negative and serious health outcomes [23]. These considerable challenges to obesity treatment may complicate the potential impact of broadband on mitigating obesity and obesity-related complications [24]. Additionally, as the dataset represents only priority counties with low broadband and high obesity, it is likely not appropriate for understanding the negative consequences of internet overuse, which the current body of obesity and broadband research highlights. As telehealth has become more prevalent, the potential to overcome some of these challenges to treat obesity via telehealth is more promising.

Sensitivity Analysis

In the sensitivity analyses controlling for outliers, we found that the main conclusions regarding the negative association between broadband subscriptions and diabetes prevalence and no association between broadband variables and obesity prevalence and preventable hospitalizations remained consistent, suggesting that these findings are robust (Table S1A-C). The variable that captured the effects of rapidly changing preventable hospitalizations bordered on significance in the diabetes model excluding outliers but was found to be significant in the model including outliers, suggesting that some of the data points excluded may have had an impact on this relationship. Obtaining further data on counties with very high to very low numbers of preventable hospitalizations, and whether there were local changes that resulted in large reductions, may help clarify this dynamic.

Disparities across Subgroups: Veterans, Persistent Poverty and Rural Populations

The differences in health outcomes across subgroups are striking, and offer a view of demographic factors associated with health inequity.

Counties with a high veteran population exhibit notably better health outcomes than counties belonging to the other groups, showcasing significantly lower diabetes and obesity rates compared to other counties. While veterans themselves may have worse health outcomes relative to the population, they reside in areas that represent more privileged populations [25], [26], [27]. Therefore the “veteran” variable may be capturing effects due to socioeconomic status, healthcare access, high insurance coverage, and racial factors rather than reflecting inherently protective factors related to being a veteran.

The trends observed in rural counties are consistent with previous work, which found that rural counties have poorer measures of almost all social determinants of health than urban counties [28]. Obesity in rural areas is approximately 6.2 times higher than in urban America [29]. Rural-urban disparities are only increasing over time, as rates worsen more in rural than in urban counties [28]. Such findings emphasize the potential importance of prioritizing outreach to rural areas in broadband support and digital literacy initiatives.

The observed connection between persistent poverty, preventable hospitalizations and diabetes rates is not surprising. Adults living in high poverty neighborhoods experience worse health outcomes overall [32]. Exploratory boxplots (Figure S2A-F) showcase that although persistent poverty-only counties are well connected, counties that experience persistent poverty and are rural are far worse connected; therefore, there might be urban pockets of persistent poverty counties that have high connectivity but still experience health disparities. The health disparities observed in persistent poverty counties may be attributed to poor insurance coverage, lack of regular medical care, and worse care continuity experienced in these neighborhoods [32], [33]. These findings

highlight the many challenges in improving health equity and provide additional support for interventions that are community specific.

The observed disparities in health outcomes across different demographic groups emphasize the need for tailored public health strategies that consider both the digital divide and consider socio-economic and environmental determinants of health. Prioritizing rural, persistent poverty counties in public health outreach and broadband support initiatives may help limit growth of the digital divide and improve health equity in a targeted manner. The demonstrated relationship between increased broadband subscriptions and decreased rates of diabetes and preventable hospitalizations underscores the potential of telehealth as a tool for improving health outcomes. This insight points towards the necessity of expanding broadband access as a public health intervention, not only to improve connectivity but also to facilitate remote healthcare delivery, which can be particularly beneficial in underserved and rural areas. Moreover, the lack of a significant relationship between broadband and obesity highlights the complexity of obesity as a public health issue and the need for innovative approaches in its management, potentially through telehealth combined with targeted interventions addressing health literacy and access to healthcare.

In general, these findings emphasize the importance of including place based digital literacy in public health initiatives; to clarify these relationships, a logical next phase of this initial investigation could be conducting an interaction analysis to understand how subgroup membership may impact the relationship between broadband and health. An interaction analysis may help elucidate how public health initiatives can maximize benefits and decrease disparities by targeting counties with these specific attributes. This analysis could also include average US counties to compare against priority counties in a difference in differences analysis, which would help control for any time trends present that may be influencing the results. As broadband access increases, ensuring that populations are equipped with the knowledge and skills to utilize digital health resources effectively becomes paramount. This includes understanding how to access and use telehealth services, which can play a crucial role in managing chronic conditions, reducing preventable hospitalizations, and overall improving public health.

Broader Implications

These findings underscore the need for healthcare policies that prioritize expanding broadband infrastructure and access in rural and persistently impoverished counties, where health disparities are more pronounced. While expanding broadband access in these regions supports improved healthcare delivery via telehealth and addresses a critical social determinant of health, it is only part of a broader set of solutions needed to improve health outcomes. The formative association between increased broadband access and decreased diabetes prevalence suggests that broadband infrastructure could be a crucial factor in chronic disease management enabling greater access to telehealth, remote monitoring, and digital health resources. However, broadband alone is insufficient; additional factors such as digital literacy, local healthcare policies, socio-economic conditions, and community-level interventions are equally critical in addressing these disparities. By integrating broadband expansion efforts with new targeted government initiatives and complementary strategies addressing these factors, policymakers can more effectively improve healthcare access in underserved areas. Moreover, focusing on counties with persistent poverty and rural characteristics, where health outcomes are significantly worse, allows the deployment of broadband resources to act as a foundation for reducing disparities in healthcare access and outcomes when combined with broader public health interventions.

Limitations

There are several important limitations of this study to consider. First, the study focuses on trends in priority counties, so the results are not generalizable to the broader US population. However, FCC data sets provide detailed variables and longer time frames, making them particularly valuable for understanding broadband's impact in underserved regions and offering insights that may inform targeted interventions in similar contexts. Additionally, experts have speculated that the FCC broadband data is likely overestimated, and that broadband rates are considerably lower than estimated particularly in rural areas [35]. If subscription rates are lower than reported and biased in rural areas, the relationship between broadband and health outcomes in these areas may be even stronger than detected in this analysis. Though the binary persistent poverty and primary care physician shortage covariates may have captured some economic and resource related effects, including potential confounders to more specifically capture these effects may be helpful – for example, including median household income, percentage of population with insurance, number of hospitals in the county, median education level etc. For example, while a shortage of primary care providers may serve as a proxy for limited access to care, incorporating specific information on access to healthcare and local policies would offer deeper insight into the mechanisms through which broadband may influence health outcomes, and how these dynamics may be different in different contexts. Including such confounders could provide valuable context for a further examination of counties which experienced dramatic decreases in hospitalizations over a short period, how this was achieved, and the potential role of broadband in these processes. As more data is released, a better picture of which health outcomes stand to improve the most from broadband access and telehealth will emerge. Furthermore, though all data is at the county level, preventable hospitalizations are specific to Medicare beneficiaries, and health outcomes data is restricted to adults, so the sample may not be applicable to all members of the population. The broadband subscription data reflects a 5-year time span, and consecutive datasets contain 4 out of 5 years of overlapping data so changes over time become smoothed and are not as evident. In terms of the study sample, it is important to note that shifts in county lines and population shifts were not considered in this analysis.

Finally, this data comes from pre-COVID-19 years, and the healthcare and broadband landscape has changed dramatically. COVID-19 likely had an impact on all variables and the enduring effects of the pandemic are not fully understood. As more data is released, we can better consider how the pandemic may have influenced this relationship.

Conclusions

Digital infrastructure can play a critical role in health equity by enabling better access to telehealth services, health information, and remote monitoring, particularly in underserved areas. This study found a significant association between increased broadband subscriptions in FCC priority counties and reduced rates of diabetes, while no significant relationship was identified between broadband access and obesity rates or preventable hospitalizations. These findings are centered on FCC priority counties, which may have unique characteristics that differ from other regions with varying levels of broadband access or health challenges. These results suggest that public health initiatives that prioritize improvement of broadband infrastructure and literacy could contribute to improved health outcomes in these underserved regions. Further research into this relationship, effects over longer periods of time, and focusing on interactions in rural and poverty-stricken areas (in which this study predicted significantly worse health outcomes), will help target public policy to provide relief for areas the most affected by disparities in healthcare access and quality. As we continue to progress through an increasingly digital healthcare world, broadband connection will continue to become increasingly more important.

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Data Availability

The cleaned data used in this analysis is available in the Multimedia Appendix. The variables used to build this dataset were originally published in the US Census American Community Survey (ACS) five year estimates table S2801 [\[12\]](#), the FCC's Form 477 and Priority and Rural Priority 2017 list [\[3\]](#), [\[14\]](#), the CDC's US Diabetes Surveillance System [\[14\]](#), and the Centers for Medicare and Medicaid Service's Mapping Medicare Disparities by Population Datasets [\[16\]](#).

Author Contributions

Conceptualization: RG, MvF, AM

Data curation: RG

Formal analysis: RG, MvF

Funding acquisition: Not applicable

Investigation: RG, MvF

Methodology: RG, MvF

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Resources: AM, MM

Software: RG

Supervision: AM, MM

Validation: RG, MvF

Visualization: RG

Writing – original draft: MvF, RG

Writing – review & editing: MvF, RG

No AI was used in any portion of this manuscript.

Conflicts of Interest

None declared.

Abbreviations

ACS: American Community Survey

AMA: American Medical Association

CDC: Centers for Disease Control and Prevention

CI: Confidence Interval

FCC: Federal Communications Commission

FIPS: Federal Information Processing Standard Publication

OR: Odds Ratio

PCP: Primary Care Physician

PCPS: Primary Care Physician Shortage

PQI: Prevention Quality Indicator

SD: Standard Deviation

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SUPPLEMENT
Broadband Variable Computation

The percent advanced speed and download speed variables were generated from the FCC Fixed Broadband Deployment Form 477 dataset, while the percent of broadband subscriptions was extracted from American Community Survey (ACS) 5-Year Estimates. 5-year ACS data comprises data collected over 60 months, so are period estimates rather than single point in time estimates. The 5-year estimates were chosen for analysis as they contain the largest sample size and are the most reliable of the ACS estimates [13]. However, consecutive year estimates contain mostly overlapping data, so they are reported as the period of time over which they are collected. While the 5-year estimates are less likely to show year-to-year fluctuations and reveal trends in time, they have a much higher statistical reliability than 1-year estimates and cover far more areas, particularly for small geographic areas and small population subgroups, which are the focus of this paper.

Download speed ratio is the ratio of the county median of maximum advertised download speed to the maximum national download speed of 1000 Mbps. Percent broadband subscriptions is the percentage of households in a county with broadband subscriptions, calculated as the number of broadband subscriptions minus dial-up only subscriptions divided by households in the county. Percent advanced speeds is the percentage of households in a county with download speeds greater than 25 Mbps (the minimum threshold required for a stable connection) [14]. The percentage of households with download speeds greater than 25 Mbps and the download speed ratio were computed at the county level across census FIPS blocks using historical data from Form 477 [15].

Sensitivity Analysis for Correlation Matrices

The correlation matrices explore both Pearson's and Spearman's correlation matrices to investigate relationships between continuous variables, and compare the correlations both with and without outliers (Figure S1A-D). Overall, the relationships appear highly robust to inclusion and exclusion of outliers and across correlation type, suggesting linear, monotonic and negative relationships between all health outcomes and percent subscriptions. Speed appears to have a negative monotonic relationship with preventable hospitalizations as well.

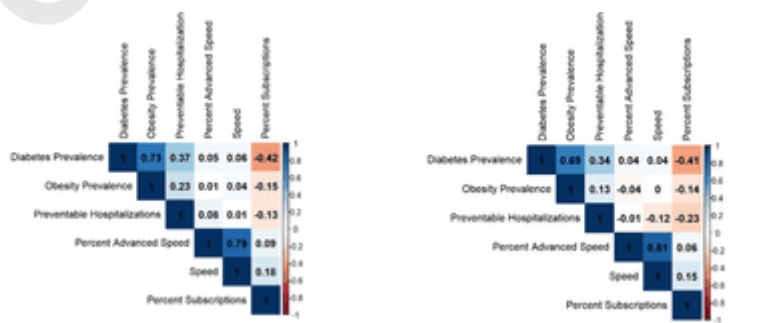


Figure S1A.

Pearson's correlation matrix of relationships between continuous variables including averages across all 187 FCC priority counties (including the 16 counties identified as potential outlier) and over time periods (2013-2020).

Figure S1B.

Spearman's correlation matrix of relationships between continuous variables including averages across all 187 FCC priority counties (including the 16 counties identified as potential outlier) and over time periods (2013-2020).

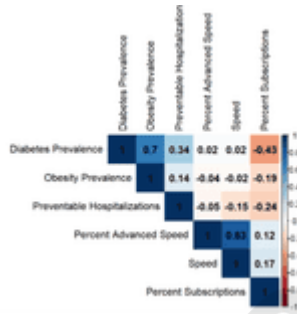
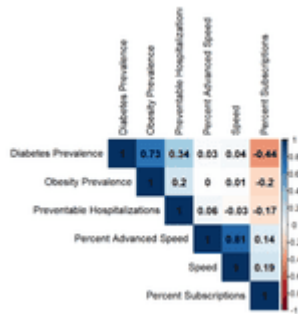


Figure S1C.

Pearson's correlation matrix of relationships between continuous variables including averages across 171 FCC priority counties (excluding the 16 counties identified as potential outlier) and over time periods (2013-2020).

Figure S1D.

Spearman's correlation matrix of relationships between continuous variables including averages across all 187 FCC priority counties (including the 16 counties identified as potential outlier) and over time periods (2013-2020).

Feature Selection

Possible features that were theorized to be important included percent broadband subscription, percent households with broadband subscriptions over 25 Mbps, maximum download speed, high veteran population, a categorical year variable to create fixed effects for each year, and the following binary indicator variables: rural, high population over 65 years old, primary care physician shortage, high American Indian/ Alaskan native population, and persistent poverty. These variables from the FCC Priority County list are important as they represent population health outcomes and demographics, access to care, and quality of care, and the broadband variables represent both access and quality of broadband.

Model selection was performed by exhaustive search using the `regsubsets()` function in R, in which subsets of all 12 theoretically important predictor variables were tested for the best fitting model.

The number of features to be included was selected based on high R^2 and low Schwartz's information criterion (BIC) values; given the optimal number of predictors, the corresponding features were identified in the function output and included in the final regression model. Even if time was not selected as important, time period indicator variables were included in all models to control for the repeated measures design.

Outlier Exclusion

Potential outlying observations for continuous variables were screened via the `identify_outliers()` function in R. After initially fitting models on all data, we also screened for counties that were particularly influential on the models by identifying points with generalized leverage values and Cook's distances beyond a defined threshold. These points were then investigated and either excluded if they were suspected to be data errors (several counties had broadband speeds that decreased from, for example, 20 Mbps to 2 Mbps in the final time period).

Subgroup Comparisons

Boxplots of counties grouped by characteristics (i.e., rurality, persistent poverty status) are presented in Figure S2 for health variables and broadband measures averaged across the four time periods of data. Groups that have a high veteran population (V) have lower diabetes than groups that do not have a high veteran population, though some of this effect is lost in groups that are also rural, persistent poverty (PP), and have a high primary care physician shortage (PCPS). Counties that have only a primary care physician shortage have relatively low rates of diabetes. Rural, persistent poverty, and primary care physician short counties have the highest mean rates of diabetes, obesity, and preventable hospitalizations, and the lower broadband measures than other counties.

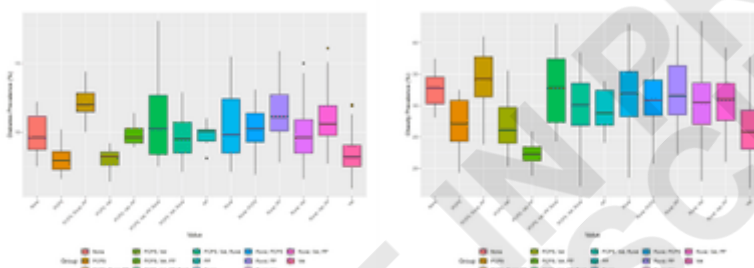


Figure S2A.

Boxplots explore the mean and variance of percent of diabetes prevalence in a county, grouping by county characteristics and averaging across FCC priority counties (N=171) and over time (2013-2020). PCPS: Primary Care Physician Shortage; PP: Persistent Poverty; Vet: Veteran.

Figure S2B.

Boxplots explore the mean and variance of obesity prevalence in a county, grouping by county characteristics and averaging across FCC priority counties (N=171) and over time (2013-2020). PCPS: Primary Care Physician Shortage; PP: Persistent Poverty; Vet: Veteran.

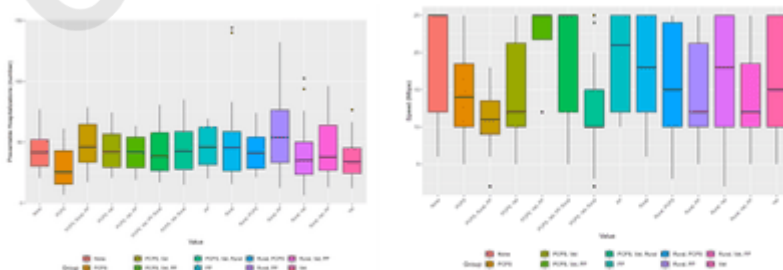


Figure S2C.

Boxplots explore the mean and variance of the number of preventable hospitalizations in a county, grouping by county characteristics and averaging across FCC priority counties (N=171) and over time (2013-2020). PCPS: Primary Care Physician Shortage; PP: Persistent Poverty; Vet: Veteran.

Figure S2D.

Boxplots explore the mean and variance of broadband speed (Mbps) in a county, grouping by county characteristics and averaging across FCC priority counties (N=171) and over time (2013-2020). PCPS: Primary Care Physician Shortage; PP: Persistent Poverty; Vet: Veteran.

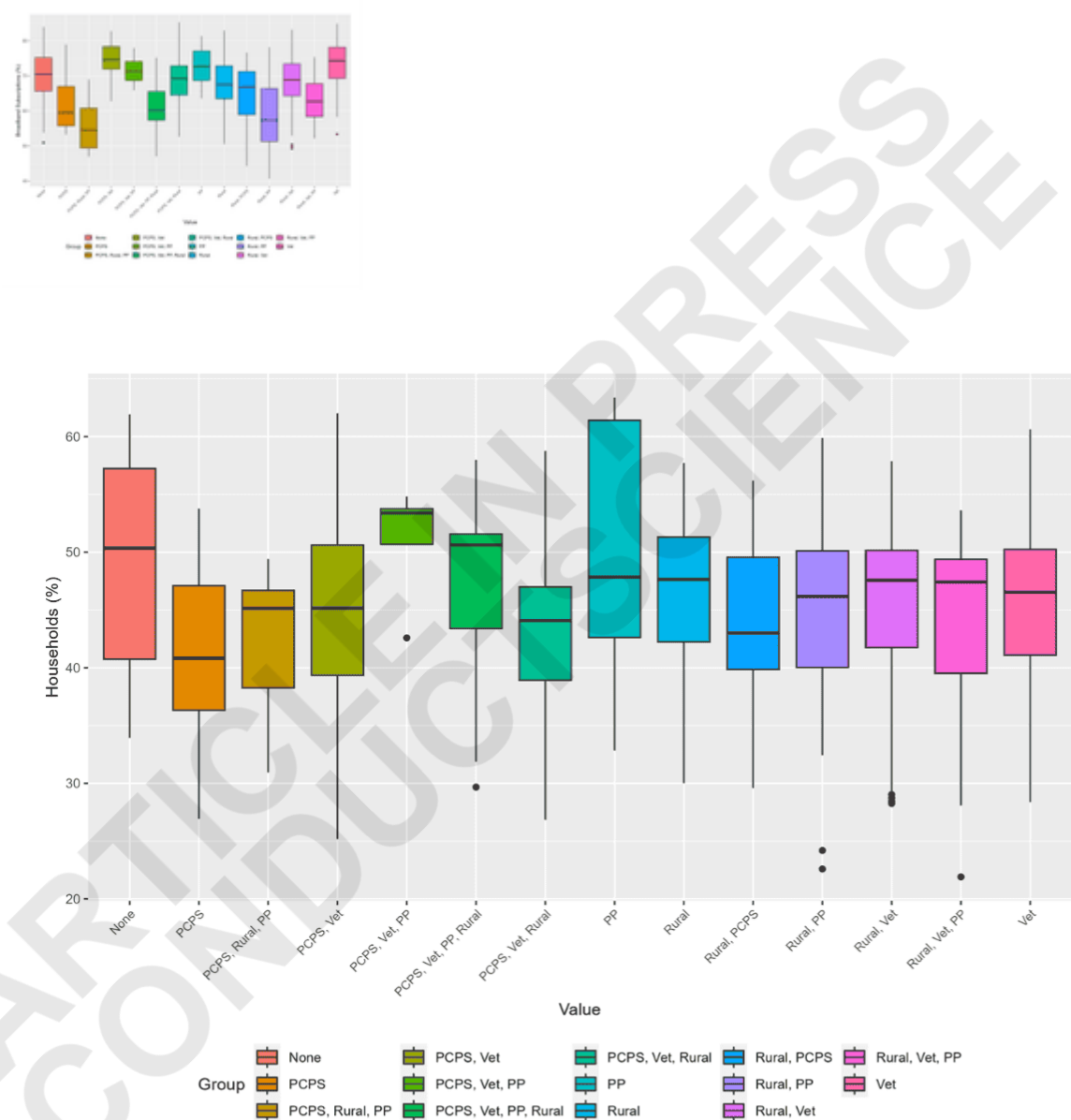


Figure S2E.

Boxplots explore the mean and variance of percent of households in a county with broadband subscriptions, grouping by county characteristics and averaging across FCC priority counties (N=171) and over time (2013-2020). PCPS: Primary Care Physician Shortage; PP: Persistent Poverty; Vet: Veteran.

Figure S2F.

Boxplots explore the mean and variance of percent of households in a county with advanced broadband speeds (> 25 Mbps), grouping by county characteristics and averaging across FCC priority counties (N=171) and over time (2013-2020). PCPS: Primary Care Physician Shortage; PP: Persistent Poverty; Vet: Veteran.

Sensitivity Analysis

Models fit with all data report fairly consistent trends. The model fit to predict diabetes prevalence reports consistent trends with the model fit after outliers were excluded - notable differences include that the dynamic hospital variable was not found to be significant in the model fit excluding outliers. Consistent with the model fit on a filtered dataset, the model predicting obesity prevalence does not find significant relationships between broadband variables and obesity rates, but instead finds that rural counties are predicted to have higher obesity rates while counties with a high veteran population are predicted to have lower obesity rates. The model predicting preventable hospitalizations is consistent with the model fit excluding outliers - persistent poverty and the last two time periods were found to be significant.

Table S1. Sensitivity analyses of relationships between broadband and health outcomes over time (2013-2020) in FCC priority counties including potential outliers (N=187), controlling for county-level characteristics.

A. Diabetes Prevalence Beta Regression	Variable	OR ^a (95% CI)
	Intercept	0.126(0.108-0.148)***
	Percent Subscriptions	0.996 (0.993-0.998)***
	Speed	1.002 (1.000-1.004)*
	Veteran	0.939 (0.907-0.972)***
	Persistent Poverty	1.094 (1.057-1.133)***
	Rural	1.155 (1.118-1.193)***
	Dynamic Hospitalizations	0.958 (0.923-0.995)*
	2014-2018	1.025 (0.985-1.067)
	2015-2019	1.028 (0.987-1.070)
	2016-2020	1.035 (0.988-1.084)
B. Obesity Prevalence Beta Regression		
	Intercept	0.378 (0.355-0.403)***
	Speed	1.002 (0.999-1.005)
	Veteran	0.915 (0.878-0.955)***

	Persistent Poverty	1.028 (0.985-1.073)		
	Rural	1.165 (1.118-1.214) ***		
	Dynamic Hospitalizations	0.994 (0.949-1.041)		
	2014-2018	1.019 (0.969-1.071)		
	2015-2019	1.040 (0.992-1.090)		
	2016-2020	1.021 (0.966-1.079)		
C. Preventable Hospitalizations Negative Binomial Regression				
		β Coefficient (95% CI)	<i>P</i> Value	Z Score
	Intercept	53.001 (41.470-67.738)	<.001	31.7
	% Subscriptions	1.001 (0.997-1.005)	.730	0.3
	PCPS	1.032 (0.990-1.076)	.133	1.5
	Persistent Poverty	1.253 (1.169-1.343)	<.001	6.3
	Dynamic Hospitalizations	0.955 (0.904-1.009)	.098	-1.7
	2014-2018	0.949 (0.892-1.010)	.102	-1.6
	2015-2019	0.560 (0.522-0.601)	<.001	-16.3
	2016-2020	0.408 (0.376-0.442)	<.001	-21.9

* , ** , *** denotes variables were found to be significant at the $P<.05$, $P<.01$, $P<.001$ levels, respectively.

...