Is there a Link between Access to Broadband and Health Outcomes?

> "Now, more than ever, broadband Internet access (BIA) must be recognized as a social determinant of health. Disparities in access should be treated as a public health issue because they affect "the health of people and communities where they live, learn, work and play." Benda, Veinot, Sieck and Ancker (2020:1123)

> "In a world where knowledge is power, the Internet has been hailed as a means of redressing longstanding inequalities in health." McKee and Stuckler (2018: 1178)

> "As health care has shifted to increasingly rely on digital tools for patient care, digital inclusion has become critical to promoting health care equity." Rodriguez, Shachar and Bates (2022: 1101)

> "Digital literacies and Internet connectivity have been called the "super social determinants of health"…" Sieck, Sheon, Ancker, Castek, Callahan, and Siefer (2021: 52).

> "Internet access is increasingly recognized as a "super determinant" of health. It plays a role in health care outcomes and influences more traditionally recognized social determinants of health, such as education, employment, and healthcare access." Turcios (2023: 1)

> "COVID-19 has magnified how internet access works as a social determinant of health." Early and Hernandez (2021: 605)

1. Introduction

We have made enormous progress in technology in recent decades including, but not limited to, broadband internet services.[1] In 2000 slightly over half (52%) of U.S. adults were using the Internet and 1% of adults had home broadband, but by 2023, 95% of U.S. adults use the Internet with 80% of adults reporting that they have broadband at home (Pew Research Center 2021). Because of such incredible growth in the availability and use of broadband, there is an increasing focus on understanding the link between broadband and outcomes like education, labor force participation, entrepreneurship, crime and property values (Dettling et al., 2018; Deller and Whitacre 2019; Conley and Whitacre 2020; Conroy and Low, 2022; Caldarulo, Mossberger

[1] Broadband is an umbrella term to describe reliable internet connections or high-speed internet access. For this study we use the terms internet and broadband interchangeably with understanding that within federal law broadband has a specific meaning: download speeds of at least 25 Mbps and upload speeds of 3 Mbps. The FCC has changed this definition to 100 Mbps download and 20 Mbps uploads, but these changes are forward looking.

and Howell 2023; Deller, Whitacre and Conroy 2023; Whitacre 2024).[2] The empirical evidence on how broadband may affect health outcomes, while growing in breath and depth, is still limited. Indeed, Early and Hernandez (2021: 605) referred to the interface between access to broadband and health "…is still an overlooked and understudied issue in public health."

The connection between access to broadband and health has largely been within the context of telehealth (e.g., Bauerly, McCord, Hulkower, and Pepin 2019; Dearinger 2020; Raths, 2020; Woodall, Ramage, LaBruyere, McLean, and Tak 2021; Broffman, Harrison, Zhao, Goldman, Patnaik, and Zhou 2023, Lipton and Pesko (2023)). Here the notion is that lack of access to health care in more rural areas, specifically significant travel distances, can be addressed through telecommunication technicalities, specifically broadband (Bell, Hung, Lòpez-De Fede, and Adams 2023). Video conferencing between patients and health practitioners can circumvent spatial distances. In addition, in home health practitioners can access the resources of larger health care facilities, such as transmitting health information, improving the quality of care. In a study of patients' satisfaction with their telemedicine experiences, Polinski, et.al. (2016: 269) found that 94 and 99 percent of respondents reported being "very satisfied" with their experiences leading the authors to conclude "that telehealth may facilitate access to care." Through this increase in access via telehealth translates, it is argued, into better health outcomes.

Unfortunately, much of the literature seeking to examine the broadband and health relationship tends to take an advocacy perspective (e.g., Benda et al. 2020; McKee and Stuckler 2018). Typical of this literature is the work of Early and Hernandez (2021), who notes that there is a significant overlap between patterns of poverty and poor health outcomes along with patterns of poverty and lack of broadband access. The proposed logical inference is that the lack of broadband access is linked to poor health outcomes. Thus, if investments are made in access to broadband, health outcomes will improve. While the logic, at face value, is appealing, the causal mechanism between access to broadband and health outcomes is purely speculative.

The pool of more rigorous literature aimed at testing the access to broadband and health outcome relationships, however, is expanding. For example, Tian, Venugopalan, Kumar, and Beard (2021) conducted a detailed analysis of 29 quantitative studies on the impact of telehealth on health and found inconsistent results, suggesting that additional research is required. Tian et al. found substantial variation in the rigor of data collection and analytical methods, outcome

[2] Bakiskan and Kaissi (2023) show a nice summary of 55 quantitative studies on the effects of broadband on various economic outcomes from various countries.

measures, and process-related as opposed to health outcomes. For example, many earlier studies of telehealth focused on the cost-benefit from the perspective of the healthcare provider with little attention to the patient. Tian et al. (2021) generally conclude that over time, the research does suggest that telehealth can improve health outcomes, but there are too many critical factors that prevent broad generalizations. A more recent meta-analysis of 66 studies of the effectiveness of telemedicine, Ganjalie, Jajroudi, Kheirdoust, Darroudi, and Alnattah. (2022:1) concluded that "[t]elemedicine was effective in improving 87.5% of health resource utilization outcomes, 85% of patient outcomes, and 100% of provider outcomes." But there is a difference between using internet broadband to talk with a healthcare provider (i.e., telehealth or telemedicine) and accessing web-based health information such as WebMD, Healthline, or the National Institute for Health website, among others.

In a study of individuals in Stoke-on-Trent, England, Estacio, Whittle, and Protheroe (2019) found that access to the internet increased health literacy. Specifically, individuals with sufficient levels of health literacy were more likely to have access to the internet and use that access to gather more health information. This could be e-mail correspondence with healthcare providers (a form of telehealth) or access to healthcare-focused websites. Here, increased health literacy should lead to better health outcomes. The authors were unable to assess, however, whether the introduction of internet access results in higher health literacy. In another study using the English Longitudinal Study of Aging, Xavier, d'Orsi, and Wardle (2013) found that internet use was quantitatively associated with cancer-preventive behavior, such as more frequent physical activity, better eating habits, and less likelihood of smoking. But the authors also found that internet use tends to be associated with younger and more educated, results which may influence the key findings: is it the characteristics of internet users or access to the internet that enhances health literacy? In a study in China, Yang and Fuling (2020) find similar patterns of increasing access to internet-based healthcare information, leading to better health practices. In the U.S., research indicates that utilizing the internet for gathering information can boost health literacy in older adults by around 12% (Bavafa et al., 2019). A survey conducted also suggests that people with dire health needs are more likely to search for health information on the Internet (Bundorf et al. 2006). Similarly, a recent study by Van Parys and Brown (2023) reveals a beneficial impact on the health of Medicare patients seeking hip or knee replacements. This improvement is largely attributed to better access to information about healthcare providers.

There are, however, factors complicating the relationship between access to and use of the internet and health outcomes (DiNardi et al., 2019; Wagner, Hu and Hibbard 2001). As noted by Amaral-Garcia et al.

(2022), implicit in much of this work is the premise that increasing access to healthcare information will result in more informed decision-making and better health outcomes. There are, however, three possible pathways to negative health outcomes. First, the growing volume of internet-based health information can lead to a potentially overwhelming flow of information. Too much information can inundate a person's ability to make informed decisions (Reutskaja, Iyengard, Fasolo and Misuraca 2020). Second, there is notable evidence that there is a significant volume of inaccurate health information online, leading to people being easily misinformed (Swire-Thompson and Lazer, 2020; Ferrara, Cresci and Luceri 2020; Dib, Mayaud, Chauvin and Launay 2022). Third, people may substitute health information from the internet for visits to health professionals. Without guidance from health professionals, people could misuse internet-sourced information, leading to poorer health outcomes.

The flood of internet-based health information, particularly on social media, during the COVID pandemic has raised concerns about the scale of misinformation (e.g., Peng, Lim, and Meng 2023; El Mikati, Hoteit, Harb, El Zein, Piggott, Melki, Mustafa, and Akl 2023). In study at the beginning of the "Wuhan Coronavirus" pandemic (the authors note that the terms "COVID-19" or "SARS-CoV-2" where not in use at the time of the study) Cuan-Baltazar, Muñoz-Perez, Robledo-Vega, Pérez-Zepeda, and Soto-Vega (2020) found that of 110 websites discussing the Wuhan Coronavirus 70% lacked any commonly accepted quality control checks generally accepted within the healthcare profession (i.e., HONcode; JAMA benchmarks; DISCERN). This led the authors to conclude that early in the pandemic there was "no quality information was available on the internet about COVID-19" (p.1). The volume of health misinformation, particularly related to COVID, has led to a substantial literature seeking to better understand the underlying sources for such misinformation (e.g., Freiling, Krause, Scheufele, and Brossard 2023; Sanford, Smith, and Blum 2023; Song, So, Shim, Kim, Kim, and Lee 2023). The question is if the growth of health misinformation on the web is detrimental to health outcomes.

A study by DiNardi, Guldi , and Sim (2019) using U.S. data finds that increased internet access increases body weight, mainly for white women, and has mixed effects on health behaviors like exercise, smoking, and drinking. The authors hypothesize that more time spent using the internet results in a more sedentary activity which could lead to increases in body weight. The authors, however, note that the connecting mechanism between access to the internet and health outcomes is mixed with evidence of increased body weight in white women, but both positive and negative effects on adult health behaviors, including physical activity, smoking, and drinking. In a complementary study of internet use and obesity in China, Chen and Liu (2022) find consistent and robust evidence that increased internet access is associated with lower incidences of being overweight. The authors suggest that the underlying mechanism is increased access to health and diet information.

In a meta-analysis of earlier work, Huang (2010) examined 40 studies examining the relationship between psychological well-being and internet use, finding a general tendency to support a positive relationship (greater internet use is associated with better mental health) but warns that the rigor of many of these earlier studies could be a concern. In an updated meta-analysis of 31 studies (18 quantitative and 14 qualitative) that explore the relationship between internet use and mental health, Forsman and Nordmyr (2017) found a preponderance of evidence that for older adult internet use was associated with at least one measure of mental health outcomes. Forsman and Nordmyr maintain that access to, and use of, the internet enhanced individual interactions as well as greater awareness and connection to community resources. A more recent qualitative synthesis of 48 studies and a meta-analysis of 19 studies, Bizzotto et al. (2023) found a consistent positive relationship between depressive symptoms and web-based help-seeking behaviors through online support groups. Here access to online support groups could be interpreted as a type of telehealth. Excessive internet use by adolescents, however, has been found to be associated with poorer mental health outcomes across the high school years (Asam, Samara, and Terry 2019; Ciarrochi et al. 2016). While the research suggests that the role of internet use in mental health varies by age, it is clear that internet use can influence mental health outcomes.

The literature seeking to better understand the interrelationships between access to broadband internet and health outcomes is evolving. Evidence suggests that telehealth (or telemedicine) can enhance health outcomes because it opens additional avenues for interactions with healthcare professionals. But at the same time the growth of health misinformation on the web has called into question the premise that increasing access to health information will necessarily lead to better health outcomes. Further, the flood of health information available on the web regardless of the quality of the information could be overwhelming users leading to more as opposed to less confusion about health. Despite the growth in the relevant literature, the access to broadband internet and health outcomes remains an open question.

To gain insights into the potential relationship between access to broadband and health outcomes, we build an empirical model based on the Social Determinants of Health (SocDH) framework. The framework, originally proposed by Whitehead and Dahlgren (1991) and Whitehead (1992), and widely promoted by the World Health Organization (e.g., WHO 2008), suggests that health outcomes can be influenced by policies aimed at addressing social and economic inequalities. While the social policy implications are beyond the scope of this study, the logical framework provides a conceptual underpinning for structuring empirical analysis. For this study, we rely on the SocDH framework underpinning the County Health Rankings project undertaken by the Wisconsin Population Health Institute in collaboration with the Robert Wood Johnson Foundation (Hood, Gennuso, Swain and Catlin 2016; Park, Roubal, Jovaag, Gennuso and Catlin 2015; Remington, Catlin and Gennuso 2015).

We follow the lead of researchers, such as Dalsania et al. (2022), who use U.S. county-level data to document that lower levels of internet access were linked to higher COVID-19 mortality rates and use U.S. county-level data to assess the impact of access to internet services and health outcomes. We use data from the County Health Rankings (CHR) combined with either the Federal Communication Commission's (FCC) Form 477 data or American Community Survey (ACS) data on broadband access.

As outlined in more detail in Table 1, the source of the health outcome data is the County Health Rankings (CHR). The original source is the Center for Disease Control's (CDC) Behavioral Risk Factor Surveillance System which is a telephone survey. As this is an ongoing survey, the 2020 data, which is what is used for this study, is a rolling average. Here, higher values of each of these three health outcomes are associated with poorer levels of health. The four health behavior measures are also drawn from the CDC, but a mixed methods approach is used, including both the telephone survey matched to administrative health data. Higher levels of each of these health behavior measures are expected to be associated with poorer health outcomes. The socioeconomic and demographic data is drawn from the Census' American Community Survey 2021 five-year averages and occupational data are compiled by IMPLAN Inc.[3] As described in more detail in the methods section, the inclusion of smaller and more rural counties in the analysis, disclosure issues around detailed occupational data become a concern and as such we take advantage of IMPLAN Inc. derived occupation data.

2. Model and Empirical Methods

[3] IMPLAN is an economic modeling system used to assess the economic impact of various activities within a specific region. It stands for "Impact Analysis for Planning," and it's often employed by researchers, policymakers, and businesses to understand how changes in one sector or industry can affect the broader economy. In addition to the economic impact modeling system IMPLAN has constructed a detailed economic database for all U.S. counties. Additional details can be found here: https://implan.com/

The formal model to be estimated can be expresses as

$$HO_j = F\left(HB_f, SE_k, CC_h, PE_z\right). \tag{1}$$

Here health outcomes (HO_j) is a function of health behaviors (HB_f), socio-economic factors (SE_k), clinical care access (CC_h), and physical environment (PE_z). As outlined in Park, Roubal, Jovaag, Gennuso, and Catlin (2015), health behaviors (with a weighting of 30%) include things such as smoking, alcohol use, diet, and exercise, among others, and socio-economic factors (with a weighting of 40%) include things like education, public safety, and poverty rates among others, and clinical care access (with a weighting of 20%) is captured by access to quality of healthcare. A fourth factor is the physical environment (weighting of 10%), which is proxied by air and water quality and housing, among others. For this study, the physical environment reflects access to broadband internet. For our study, we have three (j=3) health outcome measures, four (f=4) measures of health behaviors, five (k=5) socio-economic characteristics, and three (h=3) measures of access to clinical care. The data are for U.S. counties.

The five socio-economic measures are drawn from the U.S. Census Bureau American Community Survey, specifically the 2021 five-year averages. The percentage of the population that is nonwhite and the two poverty measures are self-explanatory, but the education and age indices are constructed using the ACS data. The Education Index captures the distribution (3^{rd} moment) of education from less than a 9^{th} grade education to an advanced degree where positive values of the index mean that lower education attainment is more likely and negative values suggest higher educational levels are more likely. The Age Index uses a similar approach where a positive value means that the age distribution is skewed younger, and a negative value means the age distribution is skewed older. Based on the health outcome framework, we expect poorer, less educated, and older populations to have poorer health outcomes.

For the clinical care access measures, we use the concentration of county employment in key healthcare professional occupations. Here we use the occupational data compiled by IMPLAN Inc.[4] A higher concentration of physicians and nurses is clearly indicative of higher levels of

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access to health care. Pharmacists are also considered “front-line” health care workers because they often have a greater frequency of interaction with local residents. As such, a higher concentration of pharmacists is indicative of greater access to health care. Finally, counselors and social workers, particularly those who focus on mental health, substance abuse, and health care more broadly, are an important piece of the healthcare access puzzle. Unfortunately, at the level of data aggregation in our primary occupational employment data source, all types of counselors and social workers are included, thus capturing some areas not directly relevant to health outcomes, such as probation officers. An important element of these occupation data is the level of interpolation to fill in disclosure issues with the data. Because we are using U.S. county-level data, including the smallest and most rural counties, disclosure issues limit the ability to use sufficiently detail Census occupational data directly. Here IMPLAN has created methods to estimate occupation employment levels for relatively refined classifications. Thus, some care must be taken when interpreting the modeling results.

All of the health behavior, socio-economic characteristics, and access to health care are control variables and of secondary interest to our focus on access to broadband. To proxy access to broadband, we use two distinct measures: self-reported internet subscripts from the American Community Survey (ACS), and the percent of the population with access to broadband. As a simple robustness test we use both the older definition of broadband (25/3 Mbps) and the more recently revised definition which increased the speed thresholds (100/10 Mbps). The latter is drawn from the Federal Communication Commission’s Form 477. While the FCC data is the key source of broadband access for determining the eligibility of state and federal funding, the limitations of this data are well known (Boliek, Makuch, Matraves and Yankelevich 2019; Grubesic, Helderop and Alizadeh 2019). But until the improvement in the data mandated by the Broadband Deployment Accuracy and Technological Availability Act 2020, also known as the Broadband DATA Act, is available, national-level studies are limited to the available FCC and Census data. While we are using three measures of access to broadband as a simple robustness check on our results, one could argue that the FCC data measures access while the ACS data measures adoption. Indeed, the two FCC sourced measures (access to 25/3 and 100/10 Mbps) are highly correlated (rho=0.7038), the correlation with the ACS data is more modest (rho for 25/3 is 0.4395, and for 100/10 the rho is 0.4475).

To test the association between access to broadband and health outcomes, we estimate a simple linear model using U.S. county-level data for the lower 48 states. The model can be expressed as:

$$HO_j = \alpha + \Sigma_f \beta_f HB_f + \Sigma_k \gamma_k SE_k + \Sigma_h \theta_h CC_h + \eta BB_i + e_j \qquad (2)$$

where the dependent and control variables are as previously defined and BB_i is the ith measure of broadband. As discussed above, we have three measures of broadband:

Percent of Households with an Internet Subscription (ACS)
Percent Population with Access to 25/3 (FCC)
Percent Population with Access to 100/10 (FCC)

Note that we also use 100/10 Mbps thresholds to test if broadband speed plays a role and can be thought of as a robustness check. Each of the three broadband measures one at a time to the influence of collinearity amongst the broadband measures. Given three health outcome measures, we estimate three base models with broadband removed and then step in each broadband measure for a total of nine separate broadband augmented models.

A challenge in estimating our broadband-augmented health models is the presence of spatial spillover effects across counties. County boundaries, while a common geographic unit to collect and report data, do not necessarily reflect socio-economic boundaries. In the case of health outcomes, there are clear spatial patterns in the data with geographic clustering of poor health (Map 1). For example, high levels of the population that report fair or poor health are clustered across the southern U.S. as well as large parts of southern Appalachia.[5] This strongly suggests that the use of ordinary least squares will yield biased, inconsistent, and, at a minimum, inefficient estimates.

Within the econometrics literature that seeks to address spatial dependency (e.g., LeSage and Pace 2009) there are three fundamental approaches: the spatial dependency is not structural but rather takes more of a random pattern that complicates the error structure, the dependency is structural in the nature of the primary variable of interest the dependent variable, and the structural dependency is not only in the dependent variable but across all elements of the model. These alternative approaches are commonly referred to as a spatial error model (SEM), spatial lag model (SAR), and the spatial Durbin model (SDM).

[5] A simple Moran's Index test of spatial dependency in our three health outcome measures reveals that there are statistically significant spatial patterns within the data. For percent reporting fair or poor health the Moran's I is 0.5958 with a z-score of 125.03 (p-value 0.0001), the average number of physically unhealthy days had a Moran's I value of 0.7454 with a z-score of 156.39 (p-value 0.0001) and average number of mentally unhealthy days had a Moran's I value of 0.8238 with a z-score of 172.82 (p-value 0.0001).

SEM: $y = \beta X + e,\ e = \lambda We + u,\ u \sim N(0, \sigma^2 I)$ (3)

SAR: $y = \rho Wy + \beta X + e,\ e \sim N(0, \sigma^2 I)$ (4)

SDM: $y = \rho Wy + \beta X + \delta WX + e,\ e \sim N(0, \sigma^2 I)$ (5)

Here the spatial weight matrix (W) explicitly captures the spatial dependency between observations (counties) and takes the form of an *n* by *n* spatial weighting matrix of the form:

$$W = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix} \quad (6)$$

Here nonzero elements w_{ij} if observations *j* and *i* are geographic neighbors and zero otherwise. Typically, the matrix W is row-stochastic, which in linear algebra mean that w_{ij} are non-negative and each row sums to one.

From a theoretical perspective, the spatial Durbin model is not only the most general specification but also more in line with expectations. Consider, for example, the concentration of health care services (clinical care access) has a strong regional dimension that cuts across county boundaries. In other words, access to health care does not stop at the boundary of the county but rather covers a much larger area. Increasingly, particularly in more rural areas, health services are concentrated in urban cores where it is not uncommon to travel across county boundaries for services. Indeed, over time, commuting patterns between places of residence and work have been expanding further, reinforcing notions of structural spatial spillover effects (Kures and Deller, 2023). While the spatial Durbin model is the preferred specification from a theoretical perspective, we estimate the models using all three spatial specifications as a way to explore the robustness of our results. Given the structural spillover effects of the spatial lag and spatial Durbin specification, it is important to note that the impact of the control variables has two means of impacting health outcomes: the direct effect or within-county effect and the indirect which captures the spatial spillover effect of nearby counties. The direct and indirect effects combined yield the total effect.[6]

[6] Consider the general form of the spatial Durbin model which can be expressed as $y = \rho Wy + \beta x + \delta Wx + e$ and in reduced form as $y = (I - \rho W)^{-1}\beta x + (I - \rho W)^{-1}\delta Wx + (I - \rho W)^{-1}e$. Let $V(W) = (I - \rho W)^{-1}$ then write the reduced form as $y = V(W)\beta x + V(W)\delta Wx + V(W)e$. Because $V(W)$ is a matrix and not a scalar, the common approach of using point estimates to test the hypothesis as to whether or not spatial spillovers exist can lead to erroneous conclusions (LeSage and Pace 2009, p.74). Instead we

3. Results

We have two sets of results, the estimated base model where we outline the performance of the control variables (Tables 2a through 2c) and the broadband augmented models which is the focal point of the analysis (Table 3). We present each in turn.

3.1. Base Model Estimates

In Table 2a, we show the relationship between the percent fair or poor health and various county characteristics using the SEM, SAR, and SDM models. In general, the results across the three spatial estimators tend to be consistent lending a certain level of assurance in the results. Each model explains over 90% of the variation in self-reported health outcomes, which given the cross-sectional nature of our data is high, and the spatial lag parameters are statistically significant for all three models. This latter result is as expected given the Moran's I statistics outline in footnote 3 and strongly suggests that not accounting for spatial spillover effects will lead to incorrect inferences.[7]

In addition, for the SAR and SDM the nature of relationship between the controls and this particular measure of health outcome are largely consistent across both the direct (within county) and indirect (across counties or spillover) effects. For example, higher rates of smoking tend to be associated with a higher percentage of adults reporting fair or poor health. The indirect effect for the SDM model is negative, which is unexpected and inconsistent, but despite the SDM being the preferred model, this one result is not sufficient to distract from the general conclusion that smoking is linked to poorer health outcomes. Higher rates of adults with diabetes are consistently associated with poorer self-reported health outcomes as well as higher poverty rates. Somewhat unexpected, higher rates of obesity are associated with better self-reported health outcomes. It could be that obesity in and of itself does not influence perceptions of health, but rather conditions associated with obesity such as diabetes. Also, somewhat unexpected the higher the percent of adults reporting insufficient sleep is linked to better self-reported health outcomes. As expect an older population is linked to poorer health outcomes (higher values of the age index is associated with a younger population) but as education goes up people tend to report poorer

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need to use the partial derivatives to properly interpret the impact of changes to the variables. Specifically, $\frac{\partial y}{\partial x} = V(W)\beta + V(W)\delta W$ or $\frac{\partial y}{\partial x} = direct + indirect = total.$

[7] Tests of multicollinearity for the base models resulted in condition indices of the design matrix is 73.86 and only one variable, the percent of adults with diabetes, has a variance inflation factor greater than ten (11.41). Given the stability of the results across the various models, we maintain that multicollinearity is not a significant concern.

health outcomes. While the age result is as what one might expect, the relationship between education and health outcomes is less clear *a priori*.

The results for the three access to health care providers suggests that a higher concentration of physicians and nurses does not appear to be statistically linked to self-reported health outcomes, but access to pharmacists does have a positive impact on health outcomes. This later result could be explained by greater interaction people have with pharmacists relative to physicians and nurses and the ability to discuss health issues in a more relaxed setting (e.g., Look, et.al. 2024). The one variable that we find mixed results across the three models is access to counselors and social workers. For the SEM model, the estimated negative coefficient is as expect; stronger access is associated with lower rates of poor health outcomes. For the SAR and SDM models, however, the estimated coefficients tend to be positive suggesting the opposite results.

In Table 2b, we show the relationship between the average number of physically unhealthy days per month for adults and the same county characteristics using the SEM, SAR, and SDM models. The overall explanatory power ranges from 0.9267 (SAR) to 0.9744 (SEM), which is remarkably high given the cross-sectional nature of the data and all of the spatial lag parameters are statistically significant, which is again as expected given the Moran's I statistics. For brevity, we will highlight the results which largely parallel the results for fair or poor health (Table 2(a)). As expected, higher rates of smoking and diabetes is associated with higher number of physically unhealthy days, yet obesity alone has a dampening effect of this health outcome measure. Higher levels of education attainment along with an older population and poverty rates are associated with a higher number of physically unhealthy days. Again, access to physicians and nurses appears to not matter, but access to pharmacists dampens the average number of physically unhealthy days. At the same time a higher concentration of counselors and social workers appears to be associated with poorer health outcomes. Again, the results for physically unhealthy days largely overlap the results for fair and poor health outcomes.

The base model results for our final measure of health outcomes, average number of mentally unhealthy days for adults, are provided in Table 2c. Again, consistent with our other two health outcome measures, the base models explain between 80.4 and 96.4 percent of the variation in average number of mentally unhealthy days and the spatial lag parameter is statistically significant. Here higher rates of smoking, diabetes and insufficient sleep are associated with poorer mental health outcomes whereas higher rates of obesity is linked to better mental health outcomes. These results are generally consistent across all three health outcome measures. Higher levels of education tend to dampen poor mental health outcomes and as the county becomes younger the number of mentally unhealthy days tends to increase. These latter two results are unlike the results for the other two measures of health. While the relationship between age and mental health is complex, it may be the case that there has been a generational change in attitudes about reporting mental health concerns. Higher rates of youth poverty put upward pressure on poor mental health outcomes, but higher poverty rates for older people does not appear to influence mental health. The pattern of relationships with access to different types of health care appears to weakly parallel the results for the other two health measures, but the results are less consistent across the different model specification (SEM, SAR, SDM).

Overall, the results of our base control variables between the fair/poor health and physically unhealthy days overlap and are largely consistent with few unexpected results. The results for mental health also overlap the two other health measures, but there are subtle differences. Given the differences between physical and mental health, subtle differences in the performance of the control variables should not be unexpected. The consistency lends a certain level of confidence in the robustness of our base models with the mental health models perhaps being the weakest of the three.

3.2. Broadband Results

The main results of the effect of broadband on health outcomes are provided in Table 3. For brevity, we do not report the results of the control variables and summarize only the results on the broadband measures. In Table 3, we report the results for three measures of broadband access: percent of households with an internet subscription using the Census American Community Survey data; percent of the population with access to 25/3 mbps broadband from the FCC data; and percent of the population with access to 100/10 mbps also from the FCC. We include the later to explore if broadband speed plays any role in health outcomes.

For the Census based data (percent of households with an internet subscription) we find mixed results in terms of statistical significance. For the SEM estimator (the spatial dependency is treated as patterns in the error structure) the data supports the central premise: higher access to the internet results in better health outcomes across all three health measures. For the SAR model (the spatial dependency is reflected in the health outcome data), higher subscription rates do not appear to influence percent of adults reporting fair or poor heath or average number of physically unhealthy days, but has a statistically significant dampening effect on average number of mentally unhealthy days. For the SDM model (where the spatial dependency is presumed to be present in all variables in the model) we find some evidence supporting the central hypothesis that increase access to the internet results in improved health outcomes. Here the pattern is more subtle: the direct effects (or within the county) is negative, supporting the hypothesis, for all three measures but the indirect (or across counites, the spatial spillover element) is insignificant for fair or poor health and number of physically unhealthy days, but statistically significant and supporting the hypothesis for number of mentally unhealthy days. Thus, for the Census based data on internet access, the data generally supports the hypothesis but with some caveats.

Using the FCC sourced data, specifically the percent of the population with access to 25/3 mbps, we also find somewhat mixed evidence. For the SEM estimator, while the estimated coefficients are negative, supporting the core hypothesis, the level of statistical significance is less than appealing. On the other hand, the results for the SAR and SDM estimators, the results consistently support our hypothesis and this holds for all three measures of health and for direct effects (within county), indirect effects (across counties or spillovers) and total effects (direct and indirect effects combined). While the lack of statistical significance with the SEM estimator is distracting, the overall results supports the idea that increased access to the internet enhances health outcomes. The final access measure is percent of the population with access to 100/10 mbps, which is also drawn from the FCC data, provides us with the most consistent results all of which support the core hypothesis. Only the SEM estimator with mentally unhealthy days is statistically insignificant while all other results are statistically significant at generally acceptable levels.

4. Conclusions

In this study we explore the relationship between access to broadband internet and health outcomes. We find, in general, broadband availability is positively associated with better health outcomes: the decline in the share of the population with fair or poor health and the decline in the number of physically and mentally unhealthy days. While this general observation of a positive association, the results are sensitive to definition of broadband and the spatial models. For instance, using the definition of the share of the population with access to 25/3 speed or 100/10 speed, we find the positive health effects in all the health outcomes and across all the spatial models. The bottom-line finding is that at the larger regional level, the hypothesized relationship between broadband and health outcome is supported by the empirical evidence. Despite these findings care must be taken in drawing too strong of a policy conclusion. Expanding access to broadband internet can play an important role in improving health outcomes, it is not a magic bullet that will solve health disparities. It is another tool in the toolbox and could create unique opportunities for regions that are experiencing investments in broadband availability.

Although our analysis does not test specific policy options, when considering the results in light of the available literature we can infer several potential policy outcomes. First, care must be taken in not overstating the potential impact broadband may have on health outcomes. Second, the significant investment in broadband infrastructure flowing from the federal Broadband Equity, Access, and Deployment *(*BEAD*)* Program may distract from the need to invest in adoption and use policies. For many communities competing for the BEAD funding, there is concern that they may fall into a "build it and their will come" trap. Communities must be actively planning for post infrastructure investment activities. A prime example is developing educational programs around telehealth. This would involve not only new users of broadband but also local health care practitioners. Third, the level of health disinformation available on the internet is of growing concern. Educational programs at the local or regional level on how to be "smart consumers" of online health information need to be developed and implemented. An equally important part of this educational need are strategies for filtering the voluminous amount of health information available online. Concerns over health "information overload" is real and needs to be considered.

There are two fundamental limitations to the empirical approach that has been adopted for this study. First, we are using a simple cross-sectional approach and as such any time lag or time dynamic dimensions to the access to broadband and health outcomes relationship is lost. It could be a reasonable argument that there is a time delay between access to broadband and health outcomes. We would suggest that given a sufficiently large cross section, a static snapshot in time can reflect the cumulative effects of past dynamic processes. In addition, analyzing variations in the data across a sufficiently large and diverse geographic region can capture underlying dynamics and relationships that have evolved over time. The second limitation is that we do not attempt to draw any conclusions concerning causation. From this study we cannot infer that investments in access to broadband will cause certain health outcomes. Indeed, over time the theoretical arguments and empirical evidence has evolved resulting in greater uncertainty about any causal relationships between broadband and health. Thus, as with much of the relevant existing empirical literature, at best we can infer if a relationship exists and the direction of the relationship.

In terms of moving the literature seeking to better understand, and hence inform policy, the interplay between access to the internet and health outcomes a more interdisciplinary approach is required. While the literature has been rapidly expanding, it has been largely within the health literature and on face value seems reasonable. This is not to say that economists, sociologists, political scientists, educators, and even community development scholars, have not explored the key issues, these respective literatures have tended to be siloed with limited cross fertilization. The rapid expansion of broadband internet is creating significant opportunities and to fully exploit those opportunities we need a stronger interdisciplinary understanding of the core issues.

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Table 1: Variable Descriptive Statistics

	Mean	Standard I	Minimum	Maximum	Source
Health Measures					
Percent Fair or Poor Health	20.6	5.02	8.9	44.8	County Health Rankings, UW-Madison, Population Health Institute
Average Number of Physically Unhealthy Days	4.3	0.75	2.6	7.2	County Health Rankings, UW-Madison, Population Health Institute
Average Number of Mentally Unhealthy Days	4.9	0.69	3.2	7.5	County Health Rankings, UW-Madison, Population Health Institute
Broadband Measures					
Percent of Household with a Internet Subscription	80.9	7.79	37.0	97.6	US Census Buruea, American Community Survey 2021, 5-Yr Average
Percent Population with Access to 25/3	91.2	13.31	0.2	100.0	Federal Communications Commission (FCC) Form 477
Percent Population with Access to 100/10	76.0	25.01	0.0	100.0	Federal Communications Commission (FCC) Form 477
Control Variables					
Health Outcomes					
Percent Smokers	20.4	4.15	6.5	38.2	County Health Rankings, UW-Madison, Population Health Institute
Percent Adults with Obesity	35.8	4.28	16.4	51.0	County Health Rankings, UW-Madison, Population Health Institute
Percent Adults with Diabetes	10.8	2.33	5.5	21.0	County Health Rankings, UW-Madison, Population Health Institute
Percent Insufficient Sleep	36.8	3.97	25.6	49.1	County Health Rankings, UW-Madison, Population Health Institute
Socio-Economic Characteristics					
Education Index	1.1	0.69	-0.6	2.5	US Census Buruea, American Community Survey 2021, 5-Yr Average
Age Index	0.6	2.14	-2.6	4.2	US Census Buruea, American Community Survey 2021, 5-Yr Average
Percent Nonwhite	23.0	19.97	1.8	97.2	US Census Buruea, American Community Survey 2021, 5-Yr Average
Poverty Rate: Under 18 years	19.4	9.90	0.0	72.7	US Census Buruea, American Community Survey 2021, 5-Yr Average
Poverty Rate: 65 Years and Over	10.2	4.63	0.0	47.9	US Census Buruea, American Community Survey 2021, 5-Yr Average
Clinical Care Access					
Occupation: Physicians and Nurses Wage and Salary Jobs per 10K Population	17.2	12.95	0.3	262.0	IMPLAN Occupation Database
Occupation: Pharmacists Wage and Salary Jobs per 10K Population	7.1	3.75	0.0	59.0	IMPLAN Occupation Database
Occupation: Counselors and Social Worker Wage and Salary Jobs per 10K Population	36.1	17.05	6.7	255.9	IMPLAN Occupation Database

Table 2a: Base Model Percent Fair or Poor Health

	SEM	SAR			SDM		
		Direct	Indirect	Total	Direct	Indirect	Total
Intercept	-2.2760 ***	---	---	---	---	---	---
	(0.0001)						
Percent Smokers	0.2824 ***	0.2144 ***	0.0531 ***	0.2674 ***	0.2746 ***	-0.2017 **	0.0729
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0014)	(0.2687)
Percent Adults with Obesity	-0.0087	-0.1006 ***	-0.0249 ***	-0.1255 ***	-0.0176 **	-0.2331 ***	-0.2506 ***
	(0.2916)	(0.0001)	(0.0001)	(0.0001)	(0.0294)	(0.0001)	(0.0001)
Percent Adults with Diabetes	1.8032 ***	1.6357 ***	0.4046 ***	2.0403 ***	1.8118 ***	0.3719 **	2.1838 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0150)	(0.0001)
Percent Insufficient Sleep	-0.0557 ***	-0.0717 ***	-0.0177 ***	-0.0894 ***	-0.0566 ***	-0.0210	-0.0776 *
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.6203)	(0.0807)
Education Index	0.4088 ***	0.6133 ***	0.1518 ***	0.7650 ***	0.4428 ***	0.6312 **	1.0740 **
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0194)	(0.0002)
Age Index	-0.0092	-0.0435 ***	-0.0107 ***	-0.0542 ***	-0.0187 **	-0.1369 **	-0.1556 **
	(0.2313)	(0.0001)	(0.0001)	(0.0001)	(0.0320)	(0.0264)	(0.0189)
Percent Nonwhite	-0.0130 ***	-0.0074 **	-0.0018 **	-0.0092 **	-0.0156 ***	-0.0370 **	-0.0526 ***
	(0.0001)	(0.0038)	(0.0029)	(0.0036)	(0.0001)	(0.0027)	(0.0001)
Poverty Rate: Under 18 years	0.0006	0.0164 ***	0.0041 ***	0.0205 ***	0.0050 *	0.0667 **	0.0717 **
	(0.7957)	(0.0001)	(0.0001)	(0.0001)	(0.0858)	(0.0035)	(0.0037)
Poverty Rate: 65 Years and Over	0.0036	0.0230 **	0.0057 **	0.0287 **	0.0094 *	0.0949 **	0.1042 **
	(0.3914)	(0.0003)	(0.0003)	(0.0003)	(0.0503)	(0.0178)	(0.0149)
Occupation: Physicians and Nurses Wage and Salary Jobs per 10K Population	-0.0016	-0.0048	-0.0012	-0.0060	-0.0020	-0.0088	-0.0108
	(0.3619)	(0.1210)	(0.1240)	(0.1213)	(0.4244)	(0.7071)	(0.6677)
Occupation: Pharmacists Wage and Salary Jobs per 10K Population	-0.0035	-0.0545 ***	-0.0135 ***	-0.0680 ***	-0.0112	-0.1112	-0.1224
	(0.5766)	(0.0001)	(0.0001)	(0.0001)	(0.1727)	(0.1280)	(0.1194)
Occupation: Counselors and Social Worker Wage and Salary Jobs per 10K Population	-0.0023 **	0.0117 ***	0.0029 ***	0.0146 ***	-0.0005	0.0275 **	0.0270 **
	(0.0377)	(0.0001)	(0.0001)	(0.0001)	(0.7232)	(0.0085)	(0.0162)
Spatial Lag Parameter	0.8610 ***	0.2040 ***			0.8200 ***		
	(0.0001)	(0.0001)			(0.0001)		
R^2	0.9780	0.9267			0.9436		

Marginal significance or p-values in parentheses.
*** significant at 99.9 percent level.
** significantat 95.0 percent level.
* significant at 90.0 percent level.

Table 2b: Base Model Average Number of Physically Unhealthy Days

	SEM	SAR			SDM		
		Direct	Indirect	Total	Direct	Indirect	Total
Intercept	0.7730 ***	---	---	---	---	---	---
	(0.0001)						
Percent Smokers	0.0783 ***	0.2138 ***	0.0530 ***	0.2668 ***	0.2753 ***	-0.2012 **	0.0741
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0022)	(0.2897)
Percent Adults with Obesity	-0.0042 **	-0.1012 ***	-0.0251 ***	-0.1263 ***	-0.0173 **	-0.2306 ***	-0.2479 ***
	(0.0009)	(0.0001)	(0.0001)	(0.0001)	(0.0309)	(0.0001)	(0.0001)
Percent Adults with Diabetes	0.2042 ***	1.6362 ***	0.4056 ***	2.0418 ***	1.8085 ***	0.3766 **	2.1850 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0097)	(0.0001)
Percent Insufficient Sleep	-0.0004	-0.0716 ***	-0.0178 ***	-0.0894 ***	-0.0561 ***	-0.0251	-0.0811 *
	(0.7891)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.5778)	(0.0856)
Education Index	0.0088 *	0.6135 ***	0.1521 ***	0.7656 ***	0.4444 ***	0.6392 **	1.0836 ***
	(0.0795)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0163)	(0.0001)
Age Index	0.0011	-0.0436 ***	-0.0108 ***	-0.0544 ***	-0.0188 **	-0.1361 **	-0.1549 **
	(0.3560)	(0.0001)	(0.0001)	(0.0001)	(0.0266)	(0.0287)	(0.0199)
Percent Nonwhite	-0.0063 ***	-0.0075 **	-0.0018 **	-0.0093 **	-0.0154 ***	-0.0373 **	-0.0527 ***
	(0.0001)	(0.0046)	(0.0039)	(0.0044)	(0.0001)	(0.0018)	(0.0001)
Poverty Rate: Under 18 years	0.0025 ***	0.0166 ***	0.0041 ***	0.0207 ***	0.0051 *	0.0661 **	0.0712 **
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0749)	(0.0050)	(0.0050)
Poverty Rate: 65 Years and Over	0.0020 **	0.0236 **	0.0059 **	0.0295 **	0.0096 *	0.0950 **	0.1045 **
	(0.0027)	(0.0003)	(0.0004)	(0.0003)	(0.0529)	(0.0207)	(0.0177)
Occupation: Physicians and Nurses Wage and Salary Jobs per 10K Population	0.0005 *	-0.0048	-0.0012	-0.0060	-0.0020	-0.0103	-0.0122
	(0.0742)	(0.1033)	(0.1065)	(0.1037)	(0.4535)	(0.6650)	(0.6338)
Occupation: Pharmacists Wage and Salary Jobs per 10K Population	-0.0013	-0.0540 ***	-0.0134 ***	-0.0674 ***	-0.0110	-0.1072	-0.1181
	(0.2022)	(0.0001)	(0.0001)	(0.0001)	(0.1857)	(0.1303)	(0.1233)
Occupation: Counselors and Social Worker Wage and Salary Jobs per 10K Population	-0.0001	0.0116 ***	0.0029 ***	0.0145 ***	-0.0005	0.0281 **	0.0276 **
	(0.7781)	(0.0001)	(0.0001)	(0.0001)	(0.7326)	(0.0069)	(0.0136)
Spatial Lag Parameter	0.9250 ***	0.2040 ***			0.8210 ***		
	(0.0001)	(0.0001)			(0.0001)		
R^2	0.9744	0.9267			0.9436		

Marginal significance or p-values in parentheses.
*** significant at 99.9 percent level.
** significantat 95.0 percent level.
* significant at 90.0 percent level.

Table 2c: Base Model Average Number of Mentally Unhealthy Days

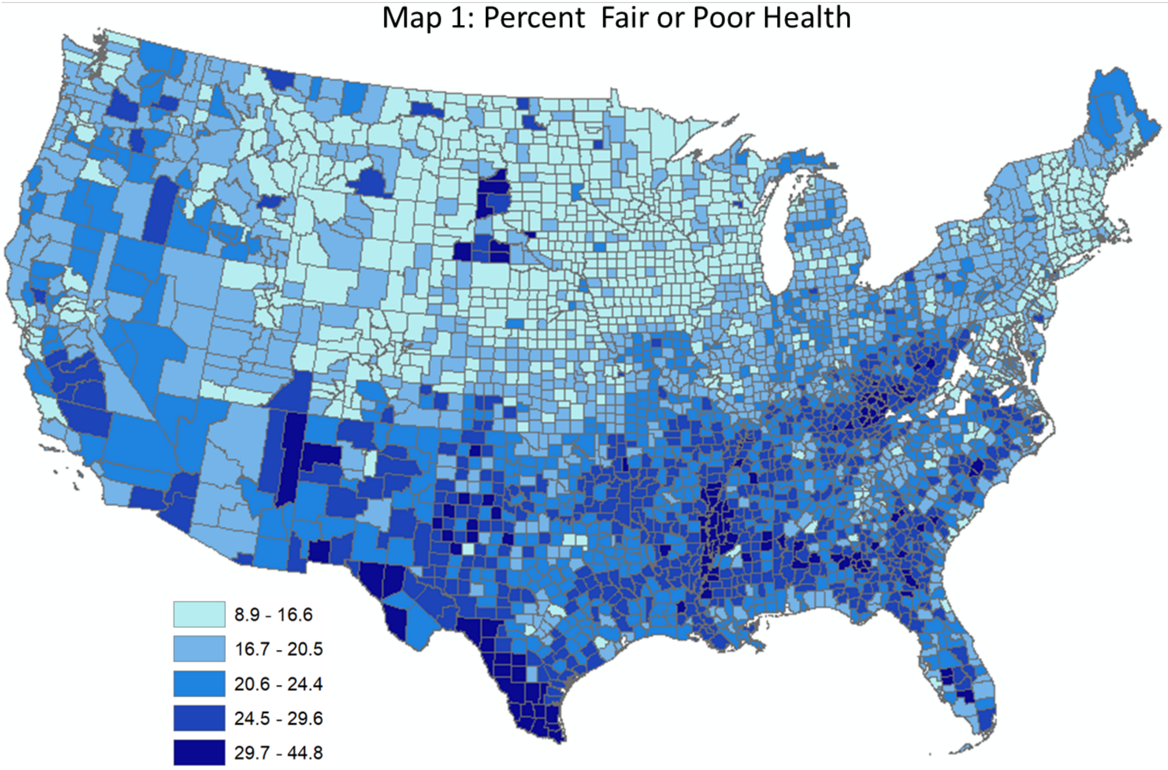
	SEM	SAR			SDM		
		Direct	Indirect	Total	Direct	Indirect	Total
Intercept	2.1808 ***	---	---	---	---	---	---
	(0.0001)						
Percent Smokers	0.0775 ***	0.0502 ***	0.0605 ***	0.1107 ***	0.0759 ***	-0.0292	0.0466 **
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.1220)	(0.0188)
Percent Adults with Obesity	0.0002	-0.0167 ***	-0.0201 ***	-0.0368 ***	-0.0017	-0.0455 ***	-0.0471 ***
	(0.8881)	(0.0001)	(0.0001)	(0.0001)	(0.2477)	(0.0001)	(0.0001)
Percent Adults with Diabetes	0.0848 ***	0.0523 ***	0.0629 ***	0.1152 ***	0.0819 ***	-0.0179	0.0639
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.6762)	(0.1556)
Percent Insufficient Sleep	0.0096 ***	0.0199 ***	0.0239 ***	0.0438 ***	0.0118 ***	0.0636 ***	0.0753 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Education Index	-0.0040	0.0390 ***	0.0470 ***	0.0859 ***	0.0064	0.1767 **	0.1831 **
	(0.4628)	(0.0001)	(0.0001)	(0.0001)	(0.3456)	(0.0281)	(0.0308)
Age Index	0.0016	-0.0052 **	-0.0063 **	-0.0115 **	0.0004	-0.0252	-0.0249
	(0.2242)	(0.0080)	(0.0082)	(0.0080)	(0.8018)	(0.1539)	(0.1829)
Percent Nonwhite	-0.0092 ***	-0.0038 ***	-0.0045 ***	-0.0083 ***	-0.0091 ***	-0.0009	-0.0100 **
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.7828)	(0.0050)
Poverty Rate: Under 18 years	0.0026 ***	0.0057 ***	0.0069 ***	0.0126 ***	0.0042 ***	0.0267 ***	0.0309 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Poverty Rate: 65 Years and Over	0.0020 **	-0.0001	-0.0001	-0.0002	0.0010	-0.0150	-0.0140
	(0.0045)	(0.9461)	(0.9480)	(0.9471)	(0.2730)	(0.2199)	(0.2791)
Occupation: Physicians and Nurses Wage and Salary Jobs per 10K Population	0.0007 **	0.0001	0.0001	0.0001	0.0010 **	0.0051	0.0062
	(0.0197)	(0.9912)	(0.9939)	(0.9927)	(0.0465)	(0.4436)	(0.3867)
Occupation: Pharmacists Wage and Salary Jobs per 10K Population	0.0002	-0.0079 ***	-0.0095 ***	-0.0174 ***	-0.0009	-0.0165	-0.0174
	(0.8539)	(0.0001)	(0.0001)	(0.0001)	(0.5695)	(0.4378)	(0.4393)
Occupation: Counselors and Social Worker Wage and Salary Jobs per 10K Population	-0.0004 **	0.0001	0.0001	0.0001	-0.0007 **	-0.0050 *	-0.0057 *
	(0.0224)	(0.9987)	(0.9959)	(0.9972)	(0.0043)	(0.0886)	(0.0653)
Spatial Lag Parameter	0.9350 ***	0.5810 ***			0.8900 ***		
	(0.0001)	(0.0001)			(0.0001)		
R^2	0.9645	0.8042			0.8647		

Marginal significance or p-values in parentheses.
*** significant at 99.9 percent level.
** significantat 95.0 percent level.
* significant at 90.0 percent level.

Table 3: Broadband Impact on Health Percent with Access

	Percent Fair or Poor Health	Average Number of Physically Unhealthy Days	Average Number of Mentally Unhealthy Days
Percent of Households With an Internet subscription (ACS)			
Spatial Error	-0.0139 ***	-0.0011 **	-0.0011 **
	(0.0001)	(0.0266)	(0.0391)
Spatial Lag			
Direct	-0.0027	0.0006	-0.0015 *
	(0.5420)	(0.4242)	(0.0503)
Indirect	-0.0007	0.0003	-0.0018 **
	(0.5430)	(0.4248)	(0.0497)
Total	-0.0034	0.0010	-0.0033 **
	(0.5421)	(0.4243)	(0.0498)
Spatial Durbin			
Direct	-0.0111 **	-0.0013 **	-0.0020 **
	(0.0012)	(0.0309)	(0.0018)
Indirect	0.0309	-0.0025	-0.0160 **
	(0.2545)	(0.6856)	(0.0450)
Total	0.0198	-0.0038	-0.0180 **
	(0.4916)	(0.5603)	(0.0310)
Percent Population with Access to 25/3 (FCC)			
Spatial Error	-0.0021	-0.0003	-0.0003
	(0.1019)	(0.2109)	(0.1756)
Spatial Lag			
Direct	-0.0039 **	-0.0011 **	-0.0024 ***
	(0.0285)	(0.0010)	(0.0001)
Indirect	-0.0010 **	-0.0006 **	-0.0027 ***
	(0.0272)	(0.0009)	(0.0001)
Total	-0.0049 **	-0.0016 **	-0.0051 ***
	(0.0280)	(0.0009)	(0.0001)
Spatial Durbin			
Direct	-0.0035 **	-0.0008 **	-0.0013 ***
	(0.0195)	(0.0002)	(0.0001)
Indirect	-0.0210 *	-0.0096 ***	-0.0166 ***
	(0.0521)	(0.0001)	(0.0001)
Total	-0.0244 **	-0.0104 ***	-0.0179 ***
	(0.0347)	(0.0001)	(0.0001)
Percent Population with Access to 100/10 (FCC)			
Spatial Error	-0.0017 **	-0.0002 *	-0.0001
	(0.0224)	(0.0534)	(0.3629)
Spatial Lag			
Direct	-0.0049 ***	-0.0013 ***	-0.0016 ***
	(0.0001)	(0.0001)	(0.0001)
Indirect	-0.0012 ***	-0.0007 ***	-0.0018 ***
	(0.0001)	(0.0001)	(0.0001)
Total	-0.0061 ***	-0.0020 ***	-0.0034 ***
	(0.0001)	(0.0001)	(0.0001)
Spatial Durbin			
Direct	-0.0022 **	-0.0006 **	-0.0006 ***
	(0.0052)	(0.0084)	(0.0001)
Indirect	-0.0121 **	-0.0063 **	-0.0083 ***
	(0.0210)	(0.0081)	(0.0001)
Total	-0.0143 **	-0.0069 **	-0.0089 ***
	(0.0102)	(0.0064)	(0.0001)

Marginal significance or p-values in parentheses.
*** significant at 99.9 percent level.
** significantat 95.0 percent level.
* significant at 90.0 percent level.


Map 1: Percent Fair or Poor Health
8.9 - 16.6
16.7 - 20.5
20.6 - 24.4
24.5 - 29.6
29.7 - 44.8