Body Weight and Internet Access: Evidence from the Rollout of Broadband Providers

Mike DiNardi
Department of Economics, University of Connecticut
michael.dinardi@uconn.edu

Melanie Guldi
Department of Economics, University of Central Florida
mguldi@ucf.edu

David Simon*
Department of Economics, University of Connecticut

January 2017

JEL: I12, I18, D8
Keywords: Obesity, Exercise, Health, Information

Abstract:
Obesity has become an increasingly important public health issue in the United States and many other countries. Hypothesized causes for this increase include declining relative cost of food and a decreasing share of the population working in labor-intensive occupations. We hypothesize that the Internet, via increased information and expansion of peer networks, may also influence the obesity rate. Theoretically, increases in information should lead to more optimal consumer choices. At the same time, greater networking opportunities available through the Internet may result in peers having greater influence over positive or negative health behaviors. While the information effect could decrease the likelihood of obesity, peer effects on health behaviors may work in either direction. We use the rollout of broadband Internet providers as a plausibly exogenous source of variation in Internet use to identify the effects. We show that greater broadband coverage increases body weight and has both positive and negative effects on modifiable adult health behaviors including exercise, smoking, and drinking. These effects are strongest for white women.

*Mailing address of corresponding author: David Simon, Department of Economics, 365 Fairfield Way, U-1063, Storrs, CT 06269-1063.
We thank David Slutsky and participants of the 2016 Southern Economic Association Conference for their helpful comments on this paper.

Economists have long hypothesized that information is an important part of choice theory (Stigler, 1961) and it is reasonable to assume that increases in access to information brought about by the Internet, which has transformed the way consumers acquire information, would improve health decisions and consequently health outcomes. However, this is not necessarily the case: consumers may substitute information from the Internet for visits to health professionals, resulting in exposure to lower quality health information (Wagner, Hu, and Hibbard, 2001).[1] Similarly, individuals who spend too much time online may experience the negative health consequences of a sedentary lifestyle (Owen, Healy, Matthews, and Dunstan, 2010). Networking through the Internet could alter health-related behaviors that have been shown to be influenced by peer effects including: positive health behaviors such as exercising (Carrell, Hoekstra, and West, 2011); or negative behaviors such as drinking alcohol, smoking, or using illegal drugs (Kremer and Levy, 2008; Lundborg, 2006).[2] In this paper, we explore the relationship between Internet access and adult health with a focus on a negative health condition that has increased in the United States concurrently with Internet access: adult obesity.

Access to online health information has grown over time. Use of the Internet as a key source of this information has become increasingly common as consumers turn to websites, discussion boards, and social media. For example, the number of unique visitors to WebMD, an online publisher of health information, increased from 1.7 million in December 1999 to a monthly average of 40.8 million in the third quarter of 2007.[3] Data from the Pew Research Center's Internet and American Life Project shows Internet use among adults increased from 46% in March 2000 to 75% in December of 2007. Over the same period, the share of Internet users who ever looked for health information online increased from 55% to 75%. Broken down by gender, 61% of women and 47% of men reported using the Internet to look for health information in 2000 and this increased to 81% of women and 68% of men by 2007.[4] This suggests that women may engage with online health information more readily than men.

[1] Additionally, without expert guidance, the large quantity of information available could lead consumers to accidently misuse the information they do receive.
[2] Additionally, the Internet facilitates illegal drug transactions via the "dark web". http://www.newsweek.com/drugs-dark-web-silk-road-488957 Accessed October 13, 2016.
[3] http://investor.shareholder.com/wbmd/releasedetail.cfm?releaseid=249537&CompanyID=HLTH . http://investor.shareholder.com/wbmd/releasedetail.cfm?releaseid=274852&CompanyID=WBMD
[4] Data available from http://www.pewInternet.org/files/2014/01/Usage-Over-Time-_May-2013.xlsx. Accessed June 20, 2016.

We use the rollout of broadband providers across counties in the United States during the 2000s as a plausibly exogenous proxy for Internet use. Similar identification strategies relying on the rollout of a policy or new technology have been used to estimate the effects of the food stamp program (Almond, Hoynes, and Schazenbach, 2011; Hoynes and Schazenbach, 2009), the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) (Hoynes, Page, and Stevens, 2011), community health centers (Bailey and Goodman-Bacon, 2015), and, of particular relevance to this work, electricity (Bailey and Collins, 2011), broadcast television (Gentzkow, 2006), and broadband Internet (Bhuller et al, 2013; Bellou, 2013; Guldi and Herbst, 2017; Kolko, 2012). As discussed above, during the period of broadband rollout the consumption of information on Web MD increased 20 fold, suggesting a relationship between broadband availability and the consumption of online health information. An existing body of work examines the relationship between increased use of the Internet to search for health information and the demand for health services,[5] but less research focuses on whether Internet availability directly affects health outcomes. The research that has been conducted is limited by time period, sample size, or is purely descriptive.[6] Given that the Internet is increasingly used as a clearinghouse for health information,[7] and that this appears to have accelerated with the advent of widespread high speed access, understanding whether broadband access affects health outcomes is of great importance to understanding aggregate public health trends.

To investigate the relationship between Internet and health, we focus on body weight as our primary health outcome. Body Mass Index (BMI) and obesity are natural measures of population health because obesity and the rising share of overweight individuals is an increasing public health concern in many countries including the United States (Cawley and Meyerhoefer, 2012). Weight is a health outcome modifiable through behavior: time use, diet, exercise, and the utilization of weight loss products all directly influence BMI. Likewise, consumers' decisions related to these products are all potentially affected by Internet availability. While much research has been devoted to understanding weight gain over time, little work has examined the relationship

[5] We describe this work in more detail in the Background section.
[6] For example, Bessière *et al.* (2010) use a random sample of the U.S. population, but their study only covers two years.
[7] Amante et al (2015) provide evidence that individuals search for health information online, especially when it is difficult to access this information from health care providers.

between technology and body weight.[8] We also look at modifiable health behaviors including exercise, smoking, and drinking to provide evidence on the pathways by which Internet access affects weight gain. Ours is the first paper we are aware of to directly estimate the effect of the rollout of broadband service on health. We find that the expansion of broadband coverage is associated with increases in the average BMI and obesity rates of women and that these effects are particularly salient for white women. These results suggest technology is an important part of the obesity discussion.

Conceptual Framework

The preponderance of health information available online increases the average consumer's information set. Microeconomic theory predicts that this would improve the efficiency of consumer health decisions, assuming the information is correct. The quality of the health information discovered online, however, is variable. At one end of the quality spectrum are sources that provide correct and timely information. At the other end, information may be inaccurate, misleading, and potentially dangerous (Impicciatore et al, 1997; Akatsu and Kuffner, 1998; Donald, Lindberg, and Humphreys, 1998; McLellan, 1998; Biermann et al, 1999; Purcell, Wilson, and Delamothe, 2002).[9,10] Poor health information, or overwhelming amounts of information,[11] may lead consumers to forgo visits to professionals when more reliable advice is in fact needed. With this in mind, there are opposing viewpoints regarding how online information influences the consumption health services. Some researchers find online health information is a complement to health services (Suziedelyte, 2012), and others find it serves as a substitute (Wagner, Hu, and Hibbard, 2001). Although individuals may use online resources with the intent to make informed health-focused lifestyle changes, the potential difficulty in assessing quality of this information

[8] There is a growing body of work examining the effectiveness of smart phone applications and wearable technology (for example, Jakicic et al, 2016). These technologies, however, were largely developed after the period we consider.
[9] The issue of health information quality is so pervasive that the U.S. National Institutes of Health even has a webpage with resources to help consumers evaluate the quality of health-related websites. See https://nccih.nih.gov/health/webresources. Accessed August 18, 2016.
[10] The issue of quality is particularly salient in the work of Culver, Gerr, and Frumkin (1997), who analyze messages from an online medical discussion group. They find 89 percent of the messages were authored by users without professional training, one-third of the messages were inconsistent with conventional medical practices, and only 9 percent of the medical information provided by those without professional training contained a published citation. Similarly, Biermann et al (1999) find 35 percent of websites with medical information about Ewing's sarcoma did not contain peer-reviewed sources, and some pages contained incorrect or misleading information.
[11] Some argue there is a glut of disorganized health-related information online (Donald, Lindberg, and Humphreys, 1998; Berland et al, 2001; Purcell, Wilson, and Delamothe, 2002).

may curb their ability to improve own health. Beyond direct health information effects, use of the Internet may also affect health through social networks.

Background

Media, Internet Access, and Socioeconomic Outcomes

There is a rich literature documenting the influence of media on socioeconomic outcomes. Researchers have found evidence that the introduction of broadcast television to a market leads to drops in voter turnout (Gentzkow, 2006), and improvements in test scores (Gentzkow and Shapiro, 2008). Others have found that the variety of television programming can influence political outcomes (DellaVigna and Kaplan, 2007), fertility (Jensen and Oster, 2009; La Ferrara, Chong, and Duryea, 2012; Kearney and Levine, 2015a; and Trudeau, 2015), and can affect child outcomes (Kearney and Levine, 2015b). Other researchers have examined the increasing availability of high speed Internet and found it to be associated with improvements in wages and labor market opportunities (Akerman, Gaarder, and Mogstad, 2013; Atasoy, 2013; Dettling, 2016; Kolko, 2012). Additionally, the rollout of broadband has been linked with a wide variety of other outcomes including: increases in voter turn-out (Poy and Schuller, 2016); marriage market matching (Bellou, 2015; Potarca, 2016); reductions in teen fertility (Guldi and Herbst, 2017); and increased incidence and reporting of sex crimes (Bhuller et. al, 2013). Complementing this other work, some researchers have explored the relationship between the Internet and health outcomes (Bessière *et al*., 2010) or the demand for health care services (Baker *et al*., 2003; Suziedelyte, 2012; Wagner, Hu, and Hibbard, 2001). Yet, no paper has examined the potentially causal relationship between broadband expansion and obesity, a prominent health concern in many countries.

Obesity

Since 1980, the world obesity rate has doubled and today most of the world's population lives in countries where being obese is more likely to cause death than being underweight.[12] Figure 1 demonstrates the trends in the rates of obesity and overweight for U.S. adults aged 18 to 64, separately by race and gender, from 1990 to 2007; the obesity and overweight rates rose sharply across all race and gender subgroups, affecting a large fraction of the population. By 2007, half or

[12] http://www.who.int/mediacentre/factsheets/fs311/en/ Accessed September 1, 2016.

more of each group is classified as overweight. In response to these alarming trends, obesity has been declared as one of the leading problems in public health in the United States and other developed countries. The health costs of obesity are estimated to be at least 9.1%, or as high as 20.6% of total health costs in the U.S., suggesting substantial room for cost savings through interventions that stem the cause of weight gain (Cawley and Meyerhoefer, 2012; Finkelstein et al, 2009).[13]

Central explanations for the increase in American obesity are changes in food consumption or calorie expenditures. Prior work suggests that important factors in explaining the rise include the decreasing relative cost of food, the shift away from manual labor and to more sedentary work, increasing maternal labor supply, and the shift to a more sedentary lifestyle (Cawley, 2011).[14] Additional work suggests that a peer's body weight in an individual's social network may influence their own body weight, suggesting obesity may be contagious (Christakis and Fowler, 2007; Cunningham, Vaquera, Maturo, and Venkat Narayan, 2012; Fletcher, 2011). Last, other work suggests that technological change may be underlying these other proposed causes.[15]

Theoretically, as we describe in our Conceptual Framework section, the effect of Internet access on behavioral and environmental factors related to obesity remains ambiguous. Improved information on the negative health consequences of obesity, means to achieve a healthy weight, and access to social networks that promote healthy lifestyles could decrease obesity. At the same time, false information and access to social networks promoting negative health choices along with the potential for increased sedentary lifestyle suggest greater access may increase obesity. This suggests that an empirical examination of the effects could provide useful information regarding the overall effect of the increasing availability of broadband Internet on obesity.

Data

To proxy for Internet access we use data on the broadband providers in a county over time. Data on broadband providers comes from the Federal Communication Commission's Form 477. This form documents the number of providers in each zip code in each year from 1999 to 2008,

---

[13] Some of these costs appear to be shifted to obese individuals. Bhattacharya and Bundorf (2009) find that obese individuals earn lower wages and that this serves to shift the cost of higher premiums onto the individual.
[14] A shift to a sedentary lifestyle is partially evidenced in the decreased availability of recreation spaces such as sidewalks and other open spaces.
[15] Lakdawalla, Phillipson, and Bhattacharya (2005) explore the role of welfare improving technological change as underlying the drop in the relative price of food and the move to more sedentary occupations, and suggest that obesity is a side-effect of these technological changes.

and is consolidated into a dataset available from the Federal Communications Commission. For the purposes of our analysis, we group zip codes to county and create population weighted variables representing the fraction of the county with at least one broadband provider.[16] Although this is not a measure of individual use, it is correlated with use and serves as a good proxy for use (Guldi and Herbst, 2017).

For data on health outcomes we use the Behavioral Risk Factor Surveillance System (BRFSS) surveys from 1999 to 2007. The BRFSS is one of the largest data sets in the US that provides information on adult health and health-related behaviors for a representative sample of non-institutionalized adults who are at least 18 years old. Interviews are conducted by state health departments, assisted by the U.S. Centers for Disease Control and Prevention, through monthly telephone interviews to collect data on health and health-related behaviors. The surveys consist of a set of standard core questions, optional modules, and state-specific questions.[17] We use the BRFSS to analyze the effects of county-level broadband availability on six outcomes covering weight and modifiable health behaviors that may affect weight and may change as a result of broadband availability. Our three weight measures are body mass index (BMI), an indicator for overweight status (BMI $\geq$ 25), and an indicator for obese status (BMI $\geq$ 30). Health behaviors include three indicator variables for any exercise activity in the last 30 days, any binge drinking events (five or more drinks in one occasion) in the last 30 days, and whether an individual currently smokes. Figure 2 demonstrates that the proportion of the population overweight rises over the same period as the proportion of the population with access to a broadband Internet provider.

Using the county geographic identifiers in the BRFSS, we match individuals to our county-level broadband availability measure in each year. We limit the sample to adults age 18-64. To look at heterogeneity in responses to Internet access across subgroups: we further stratify the sample into: white men, white women, non-white men, and non-white women. We drop observations from Louisiana due to changes in infrastructure associated with Hurricane Katrina

[16] Data can be downloaded from http://transition.fcc.gov/wcb/iatd/comp.html. The documentation from the FCC indicates that these are "lists of geographical zip codes where service providers have reported providing high-speed service to at least one customer as of December 31, [of the relevant year]. No service provider has reported providing high-speed service in those zip codes not included in this list. An asterisk (*) indicates that there are one to three holding companies reporting service to at least one customer in the zip code. Otherwise, the list contains the number of holding companies reporting high-speed service. The information is from data reported to the FCC in Form 477."

[17] The core set of questions include a set of fixed core questions asked every year and a set of rotating core questions asked every other year. We focus on weight and health behavior outcomes from the fixed core of questions, but also utilize responses regarding the intensity of exercise that are part of the rotating core of questions in 2001, 2002, 2003, 2005, and 2007.

and observations from Virginia due to a large number of unmatched zip codes in the FCC data. Finally, we drop all observations without county identifiers and those missing any demographic control variables (age, gender, race, marital status, and education). This results in an unbalanced panel of counties. Because some counties are not consistently in the sample from 1999-2007 we restrict the sample to a balanced panel of counties as a robustness check and find that our baseline results do not substantially change (see Appendix Table A1).

Table 1 shows summary statistics for the variables used in the analysis. While the average county broadband availability increased from 68.9% in 1999 to 98.2% in 2007 in the US as a whole, respondents in the BRFSS tend to be in counties with higher levels of broadband coverage with an average county-level broadband coverage of 95.6% in 1999 and 99.5% in 2007. The average age in the sample is approximately 40 years old, 67.7% are white, 58.7% are married, and 34.1% have at least a bachelor's degree.

We augment our BRFSS data with additional county-level covariates including the unemployment rate and real gross domestic product per capita. Table 2 shows the means of socio-economic characteristics for U.S. counties, the subset of counties in our sample ("BRFSS counties"), and the subset of counties not in our sample ("non-BRFSS counties"). Overall, the BRFSS counties in our sample are wealthier, more urban, more educated, and spend more on social welfare than the counties not in our sample. The counties in the BRFSS, however, represent 93.9% of the U.S. population, which suggests that the omitted counties are largely sparsely populated and our estimates represent the majority of individuals living in the U.S.[18]

Methods

We use within county changes in broadband providers to identify the impact of Internet access on health outcomes in adults. Specifically, we estimate the following:

$$1)\ Y_{icmt} = \beta + \beta_1 Coverage_{ct} + \beta_2 X_{icmt} + \gamma_c + \lambda_m + \tau_t + \epsilon_{icmt}$$

Here i indexes individuals, c indexes counties, m indexes months, and t indexes years. $Coverage_{ct}$ is the percentage of zip codes in a county with at least one broadband provider, and β_1 is the coefficient of interest. County, month of the year, and year fixed effects are represented by γ_c, λ_m, and τ_t, respectively. Including these fixed effects absorbs time invariant differences in health across counties, national differences in health specific to months of the year, and national

[18] Calculations made using Census county population estimates for 2000.

differences in health across years. Y_{icmt} is either: BMI, an indicator for overweight, an indicator for obese, or one of our other adult health outcomes of interest.[19]

In equation 1, β_1 is identified from within county changes in health that coincide with within county changes in coverage; holding national average health within a year constant. A key assumption behind the identification of β_1 is that there are no trends in health prior to the entrance of broadband providers into counties relative to those who have not yet had an entrant. In other words, this models assumes that adult health was not improving (or declining) before a county experienced a change in broadband availability (relative to counties where at that time there was no change in providers). To address this problem, we test the robustness of our results to county-specific linear time trends.[20] To further address this concern, we test whether future broadband adoption influences past adult weight outcomes.

Causal identification of β_1 also assumes that there are no contemporaneous unobserved changes in county policies, demographic composition, or characteristics that jointly induce broadband entrance and directly impact adult health. This assumption would be violated if, for example, county level policies designed to improve health also led to (or coincided) with the entrance of broadband providers. It is impossible to be entirely sure that this assumption holds, though we test it as rigorously as possible. Specifically, we add relevant time varying county and individual-level observable characteristics (represented by X_{icmt}), to see if our estimates are sensitive to controlling for variables that would likely be correlated with unobservable changes. Individual-level controls include indicators for single year of age, education (high school, some college, and 4+ years of college), and marital status. In the non-white samples, we include indicators for Hispanic and all other races, using black as our base group; and we control for economic conditions by including the county unemployment rate and real per capita income.

[19] We have also run models with year-month fixed effects (rather than separately controlling for year and month of the year), which produced similar results to our baseline specification. These results are in Appendix Table A2.

[20] While we would like to examine the trends in adult health in treated versus untreated counties before the expansion of broadband, this is nearly impossible to do in practice with the data we have. Our measure of broadband availability begins in 1999. Broadband providers, however, are present to some degree in the majority of counties observable in the BRFSS data in 1999, making it difficult to distinguish the exact starting date of treatment in these counties. Compounding this issue, not all BRFSS counties are observable in the pre-1999 era. Consequently, to buttress our assumption that the timing and degree of county broadband expansion is exogenous to county adult health we rely on the careful work of other researchers who have used the same policy instrument, some of whom have examined pre-treatment trends directly for other outcomes (Atasoy, 2013; Bellou, 2015; Guldi and Herbst, 2017; and Kolko, 2012).

Results

Body Weight

Table 3 shows our core results from the regressions of weight-related outcomes for the samples of white men and white women. Across the different outcomes, for white men the sign on our measure of broadband access are positive, but relatively small in magnitude and statistically insignificant. Overall this suggests no consistent effect of Internet availability on health for white men. On the other hand, an increase in Internet availability has robust and moderately sized effects on a variety of measures of body weight for white women.[21] Starting at column 5, for white women a 10 percentage point increase in the fraction of the population in a zip code with at least one Internet provider would increase BMI by 0.1026 and the probability of being obese by 0.006. These represent effects that are 0.39% and 3.00% of the mean, respectively.

Moving across the columns of Table 3 shows that the results are generally robust to a variety of alternate specifications such as adding demographic and county level controls. One concern in difference-in-differences type models is that there may be differential trends in health between counties that expand broadband access and those that do not. However, as can be seen in moving from column 7 to 8 of Table 3, there is little change in the coefficients after adding county linear trends.[22] Overall, we consider these estimates to be reasonably robust. We also estimated similar models for the non-white samples of men and women. These results, reported in Table 4, follow a similar pattern, though most coefficients are not statistically significant.[23]

Health Behaviors

Given these findings, we attempt to understand the mechanisms by which broadband availability affects health. If the Internet affects the information or social networks available to consumers, we should be able to see changes in health behaviors that could, in turn, result in weight gain. During our sample period, the BRFSS consistently collects information on a number of health behaviors of interest: exercise, binge drinking, and current smoking. The estimates of our model with these health behaviors as outcomes for whites are in Table 5 and show that Internet access

[21] This is consistent with women engaging with online health information to a greater degree than men, as we mention in the Introduction.

[22] While the coefficient on obesity loses statistical significance, the magnitude of the coefficient is qualitatively similar.

[23] These noisier effects on the non-white samples are potentially due to the smaller sample. An alternative explanation is that our broadband measure captures access less consistently for these group: though with somewhat larger effects on those who are effected.

increases harmful health behaviors for white men and women, presumably through a social network effect. Specifically, we see that for white women Internet access increases smoking and binge drinking, though neither measure is robust to including county linear trends.[24] Given the high calorie content of alcohol, increases in binge drinking are consistent with increased weight. While increases in exercise and binge drinking are present for white men (in models without county linear time trends), the estimated effect of exercise is larger than the effect of binge drinking, which may mean that any weight gain from drinking is overcome with the additional exercise. Table 6 contains the estimates for the nonwhite samples. Except for binge drinking these estimates do not provide statistically meaningful evidence on modifiable health behaviors.

Finally, to better understand the exercise results we look at exercise intensity as an outcome. These results are in Table 7 (whites) and Table 8 (non-whites). Here the outcome variable is either an indicator for moderate exercise (as opposed to no exercise or vigorous exercise) or vigorous exercise (relative to no exercise or only moderate exercise). For white men, the standard errors are large making it difficult to draw a firm conclusion on how Internet changes exercise intensity. For white women, we clearly see that for those who exercised, the broadband coverage increased moderate exercise and not vigorous exercise: which is consistent with a story of Internet access failing to improve health behaviors at a level of intensity that offsets the increased weight gain from drinking. One possible explanation is that white women who begin a new exercise regime in response to information about exercise on the Internet over-estimate how many calories they burn and in turn over-compensate with the calories they eat and drink. This is consistent with epidemiological work which attempts to explain why people who exercise lose less weight than expected (Miller *et al*., 1997; Thomas *et al*., 2012; Melanson *et al*., 2013; Dhurandhar *et al.*, 2014). We do not find any statistically significant effects on exercise intensity for non-white men or women.

Role of Income

An earlier literature has shown that Internet access improves wages, productivity, and growth (Kolko, 2012; Akerman, Gaarder, and Mogstad, 2013; Atasoy, 2013). Such effects are an

[24] Since smoking is an appetite suppressant, it can be associated with declines in weight. However, we take the increase in smoking as evidence for a more general story of broadband expansions causing overall worse health behaviors which in turn outweighs the benefits of decreased food consumption from smoking.

alternative mechanism by which Internet access could increase body weight. A number of studies show that the relationship between obesity and economic conditions is quite complicated.[25]

We explore the relationship between income and broadband access by adding an interaction between our broadband variable and whether the observation was in a relatively high or low income county (based on pre-period 1999 income levels). This allows for heterogeneous effects of broadband Internet access for those who are already living in affluent areas versus poorer areas. At the same time, this test helps address the criticism that broadband differentially expands into richer areas by essentially comparing separate effects of broadband in areas with similar income levels. The results in Table 9 shows that for relatively richer counties (as measured by either being above the median, or at the 80th percentile), broadband access increases weight gain and obesity; with the opposite effect for the lower income counties. We interpret these results as suggestive that less wealthy areas benefited from broadband (potentially because these areas had more to gain from the economic activity associated with broadband). This in turn suggests that there are important differences in how income interacts with broadband though income itself is not necessarily the principal channel explaining the declines in health.

Falsification Test

As Figure 2 shows, obesity rates were trending up since the 1990s and 2000s during the rollout of broadband Internet. While Figures 1 and 2 show national trends, it is possible that there is a spurious pre-trend in body weight for counties that later increase their Internet access. We conduct a falsification test by check the timing of broadband availability and changes in body weight by replacing our broadband measure with a three year lead of our broadband measure. More specifically, we estimate the following model for each of our three weight measures:

$$2)\ Y_{icmt} = \beta + \beta_1 Coverage_{ct+3} + \beta_2 X_{icmt} + \gamma_c + \lambda_m + \tau_t + \epsilon_{icmt}$$

For this analysis, we match individual-level data from the 1996-2004 BRFSS to their corresponding county-level broadband measure three years in the future.[26] All control variables in X_{icmt} and fixed effects are the same as in equation 1. Results from these regressions are reported

[25] The cross sectional relationship suggests that higher income is associated with lower levels of obesity. However, economic recessions have been known to reduce body weight in the severely obese (Ruhm, 2005). Similarly, income transfers to low income Native American adults through a casino opening, increased obesity in their children (Akee et al., 2013).

[26] For example, individual observations from Middlesex County, Massachusetts in the 1996 BRFSS are matched to the 1999 broadband measure for Middlesex County, Massachusetts.

in Table 10 (whites) and Table 11 (non-whites). Our estimates are not statistically significant for any regression in either table. Although the estimates are opposite in sign from our main results in some specifications, when the estimates are the same sign, the magnitudes are generally smaller than our main estimates (Tables 3 and 4). This test suggests that our results are not driven by a spurious correlation between broadband availability and body weight.

Conclusion

Obesity has become an increasingly important public health issue in the United States and many other countries. Hypothesized causes for this uptick include declining relative cost of food and decreasing share of the population working in labor-intensive occupations. In this paper, we hypothesize that the Internet, via information and the expansion of peer networks, may also influence the obesity rate.

We use the rollout of broadband Internet providers as a plausible source of exogenous variation in Internet use to identify the effects. We show that greater broadband coverage increases body weight and has both positive and negative effects on modifiable adult health behaviors including exercise, smoking, and drinking. A 10% increase in broadband availability increases obesity among white women by 0.006; which represents an effect of 3.00% of the mean. Referring to Figure 1, between 1990 and 2007 obesity increased by 15%; suggesting that while Internet is by no means the driving force behind this increase: it is a considerable part of the story. Our back of the envelope calculations suggest that increased medical costs from obesity due to internet access over this time came to approximately 3.3 billion.[27]

How can we explain the mechanisms behind our findings that Internet availability increases weight gain in white women? Theoretically, increases in Internet availability should lead to more optimal consumer choices. However, as we show, such choices does not necessarily mean health improves: greater networking opportunities available through the Internet may result in peers having greater influence over positive or negative health behaviors. Indeed a number of papers have linked the Internet to expanding social circles (Wellman *et al.*, 1996; Wellman and Gulia,

[27] We calculated this by multiplying our estimate of the effect of increasing obesity for white women (a 6 percentage point increase in obesity) by the change internet providers over the years of our sample (a 29.3% increase) by the population of adult white women in the US in 2005 (68,013,866). This suggests that the internet pushed 1.2 million white women into obesity. Cawley & Meyerhoefer (2012), annual cost estimates for obesity are \$3,613 (women) or \$2,739 (white); suggesting an increase in costs of approximately 3.3 billion.

1999; Wellman *et al.*, 2001; and Zhao, 2006). While a pure information effect should decrease the likelihood of obesity, peer effects on health behaviors may work in either direction. We see effects of Internet availability increasing drinking for both white men and women. At the same time we do see increases in exercise for men and women. While it is possible that increased exercise can lead to weight gain (Miller *et al*., 1997; Thomas *et al.*, 2012; Melanson *et al.*, 2013; Dhurandhar *et al.*, 2014), the large effects on exercise in white men seems to cancel out the increase in weight. For women, however, this is not the case for white women due to much smaller increases in exercise for this group. Taken together, use of the Internet appears to provide both positive and negative health benefits through greater access to information and interaction with social networks that affect health behaviors.

Compliance with Ethical Standards

The authors received no funding for this study.

The authors declare that they have no conflict of interest.

References

Akatsu, H. and Kuffner, J. 1998. Medicine and the Internet. *Western Journal of Medicine* **169**(5): 311–317.

Akee, R., Spilde, K., and Taylor, J. 2015. The Indian Gaming Regulatory Act and Its Effect on American Indian Economic Development. *Journal of Economic Perspectives* **29**(3): 185-208.

Akerman, A., Gaarder, I., and Mogstad, M. 2015. The Skill Complementarity of Broadband Internet. *Quarterly Journal of Economics* **130**(4): 1781-1824.

Almond, D., Hoynes, H. and Schanzenbach, D. 2011. Inside the War on Poverty: The Impact of Food Stamps on Birth Outcomes. *The Review of Economics and Statistics* **93**(2): 387–403.

Atasoy, H. 2013. The Effects of Broadband Internet Expansion on Labor Market Outcomes *Industrial Labor Relations Review* **66**: 315-345.

Amante D.J., Hogan T.P., Pagoto S.L., English T.M., Lapane K.L. 2015. Access to Care and Use of the Internet to Search for Health Information: Results from the US National Health Interview Survey. *Journal of Medical Internet Research* **17**(4): e106.

Bhattacharya, J. and Bundorf, M.K. 2009. The incidence of the healthcare costs of obesity. *Journal of Health Economics* **28**:649-658.

Bailey, M. J. and Collins, W. J. 2011. Did Improvements in Household Technology Cause the Baby Boom? Evidence from Electrification, Appliance Diffusion, and the Amish. *American Economic Journal: Macroeconomics* **3**: 189–217

Bailey, M.J. and Goodman-Bacon, A. 2015. The War on Poverty's Experiment in Public Medicine: Community Health Centers and the Mortality of Older Americans. *American Economic Review* **105**(3): 1067–1104.

Baker, L.B., Wagner, T.H., Singer, S., and Bundorf, M.K. 2003. Use of the Internet and E-mail for Health Care Information: Results from a National Survey. *Journal of the American Medical Association* **289**(18): 2400-2406.

Bellou, A. 2015. The Impact of Internet Diffusion on Marriage Rates: Evidence from the Broadband Market. *Journal of Population Economics* **28**(2): 265-297.

Bessière K, Pressman S, Kiesler S, Kraut R. 2010. Effects of Internet Use on Health and Depression: A Longitudinal Study. *Journal of Medical Internet Research* **12**(1):e6.

Bhuller, M., Havnes, T., Leuven, E., and Mogstad, M. 2013. Broadband Internet: An Information Superhighway to Sex Crime? *Review of Economic Studies* **80**: 1237–1266.

Biermann, J., Golladay, G., Greenfield, M., and Baker, L. 1999. Evaluation of Cancer Information on the Internet. *Cancer* **86**: 381-90.

Berland, G., Elliot, M., Morales, L., Algazy, J., Kravitz, R., Broder, M., Kanouse D., Muñoz, J., Puyol, J., Lara, M., Watkins, K., Yang, H., and McGlynn, E. 2001. Health Information on the Internet: Accessibility, Quality, and Readability in English and Spanish. *Journal of the American Medical Association* **285**(20): 2612-21.

Carrell, S.E., Hoekstra, M., and West, J.E. 2011. Is poor fitness contagious? Evidence from randomly assigned friends, *Journal of Public Economics* **95**(7-8): 657–663.

Cawley, J.H.. 2011. The Economics of Obesity. In J. H. Cawley (Ed.), *The Oxford Handbook of the Social Science of Obesity* (pp. 303-312). New York, NY: Oxford University Press.

Cawley, J. and Meyerhoefer, C. 2012. The medical care costs of obesity: An instrumental variables approach. *Journal of Health Economics* **31**: 219– 230.

Christakis, N. and Fowler, J. 2007. The Spread of Obesity in a Large Social Network Over 32 Years. *The New England Journal of Medicine* **357**: 370–379.

Culver, J. D., Gerr, R., & Frumkin, H. 1997. Medical information on the Internet: A study of an electronic bulletin board. *Journal of General Internal Medicine* **12**(8): 466–70.

Cunningham, S.A., Vaquera, E., Maturo, C.C., Venkat Narayan, K.M., 2012. Is there evidence that friends influence body weight? A systematic review of empirical research. *Social Science and Medicine* **75**: 1175-1183.

DellaVigna, S. and Ethan K. 2007. The Fox News Effect: Media Bias and Voting. *Quarterly Journal of Economics* **122**(3): 1187-1234.

Dettling, L. J. 2016. Broadband in the Labor Market the Impact of Residential High-Speed Internet on Married Women's Labor Force Participation. *Industrial and Labor Relations Review*. *In press.*

Donald, A., Lindenberg, B., & Humphreys, L. 1998. Medicine and health on the Internet: The Good, the Bad, and the Ugly. *Journal of the American Medical Association*, **280**(15): 1303-1306.

Dhurandhar, E.J., Kaiser, K.A., Dawson, J.A., Alcorn, A.S., Keating, K.D., and Allison, D.B. 2015. Predicting adult weight change in the real world: A systematic review and meta-analysis accounting for compensatory changes in energy intake or expenditure. *International Journal of Obesity*. **39**(8): 1181–1187.

Finkelstein, E.A., Trogdon, J.G., Cohen, J.W., and Dietz, W. 2009. Annual Medical Spending Attributable to Obesity: Payer- And Service-Specific Estimates. *Health Affairs* **28**(5): w822-w831.

Fletcher, J. 2011. Peer Effects and Obesity. In J.H. Cawley (Ed.), *The Oxford Handbook of the Social Science of Obesity* (pp. 303-312). New York, NY: Oxford University Press.

Gentzkow, M. 2006. Television and voter turnout. *Quarterly Journal of Economics* **121**(3): 931-972.

Gentzkow, M. and Shapiro, J.M. 2008. Preschool Television Viewing and Adolescent Test Scores: Historical Evidence from the Coleman Study. *Quarterly Journal of Economics* **123**(1): 279-323.

Grossman, M., and Kaestner, R. 1997. Effects of Education on Health. In *The Social Benefits of Education*, J. R. Behrman and N. Stacey (eds.), Ann Arbor, Mich.: University of Michigan Press.

Guldi, M. and Herbst, C. 2017. Offline Effects of Online connecting: The Impact of Broadband Diffusion on Teen Fertility Decisions. *Journal of Population Economics* **30**(1); 69-91.

Hoynes, H., Page, M., Stevens, A. H. 2011. Can Targeted Transfers Improve Birth Outcomes? Evidence from the Introduction of the WIC Program. *Journal of Public Economics* **95**(7–8): 813–827.

Hoynes, H. and Schanzenbach, D. 2009. Consumption Responses to In-Kind Transfers: Evidence from the Introduction of the Food Stamp Program. *American Economic Journal: Applied Economics* **1**(4): 109–139.

Impicciatore, P., Pandolfini, C., Casella, N., Bonati, M. 1997. Reliability of Health Information for the Public on the World Wide Web: Systematic Survey of Advice on Managing Fever in Children at Home. *British Medical Journal* **314**: 1875-79.

Jakicic, J.M., Davis, K.K., Rogers, R.J., King, W.C., Marcus, M.D., Helsel, D.H., Rickman, A.D., Wahed, A.S., Belle, S.H. 2016. Effect of wearable technology combined with a lifestyle

intervention on long-term weight loss: the IDEA randomized clinical trial. *Journal of the American Medical Association* **316**(11):1161-1171.
Jensen, R. and Oster, E. 2009. The Power of TV: Cable Television and Women's Status in Rural India. *The Quarterly Journal of Economics* **124**(3): 1057-1094.
Kearney, M. and Levine, P. 2015a. Media Influences on Social Outcomes: The Impact of MTV's 16 and Pregnant on Teen Childbearing. *American Economic Review* **105**(12): 3597–3632.
Kearney, M. and Levine, P. 2015b. Early Childhood Education by MOOC: Lessons from Sesame Street. *National Bureau of Economic Research* Working Paper No. 21229.
Kremer, M and Levy, D. 2008. Peer Effects and Alcohol Use among College Students. *Journal of Economic Perspectives* **22**(3): 189-206.
Kolko J. 2012. Broadband and local growth. *Journal of Urban Economics* **71**:100–113.
La Ferrara, E., Chong, A., and Duryea, S. 2012. Soap Operas and Fertility: Evidence from Brazil. *American Economic Journal: Applied Economics* **4**(4): 1-31.
Lakdawalla, D., Philipson, T., and Bhattacharya, J. 2005. Welfare-Enhancing Technological Change and the Growth of Obesity. *American Economic Review: Papers and Proceedings of the 179th Annual Meeting of the American Economic Association* **95**(2): 253-257.
Kremer, M., and Levy, D.M.. 2008. Peer Effects and Alcohol Use Among College Students. *Journal of Economic Perspectives* **22**(3): 189-206.
Lundborg, P. 2006. Having the wrong friends? Peer effects in adolescent substance use. *Journal of Health Economics* **25**: 214–233
McLellan, F. 1998. 'Like hunger, like thirst': patients, journals, and the Internet. *The Lancet* **352**: S39 - S43.
Melanson, E.L., Keadle, S.K., Donnelly, J.E., Braun, B., and King, N.A. 2013. Resistance to exercise-induced weight loss: Compensatory behavioral adaptations. *Medicine and Science in Sports and Exercise* **45**: 1600–1609.
Miller, W.C., Koceja, D.M., and Hamilton, E.J. 1997. A meta-analysis of the past 25 years of weight loss research using diet, exercise or diet plus exercise intervention. *International Journal of Obesity Related Metabolic Disorders* **21**: 941–947.
Owen, N., G. N. Healy, C. E. Matthews, and D. W. Dunstan. 2010. Too Much Sitting: The Population Health Science of Sedentary Behavior. *Exercise and Sport Science Review* **38**(3): 105–113.
Potarca, G., 2006. Does the internet affect assortative mating? Evidence from the U.S. and Germany. *Social Science Research* **61**: 278-297.
Poy S. and Schüller, S. 2016. Internet and Voting in the Web 2.0 Era: Evidence from a Local Broadband Policy. *IZA* Discussion Paper No. 9991.
Purcell, G., Wilson, P., and Delamothe, T. 2002. The Quality of Health Information on the Internet: as for any other medium it varies widely; Regulation is not the Answer. *British Medical Journal* **324**: 557-558.
Ruhm, C. 2005. Health Living in Hard Times. *Journal of Health Economics* **24**(2): 341-363.
Stigler, G. 1961. The Economics of Information. *Journal of Political Economy* **69**(3): 213-225.
Suiziedelyte, A. 2012. How Does Searching for Health Information on the Internet Affect Individuals' Demand for Health Care Services? *Social Science and Medicine* **75**(10): 1828-1835.
Thomas, D.M., Bouchard, C., Church, T., Slentz, C., Kraus, W.E., Redman, L.M., Martin, C.K., Silva, A.M., Vossen, M., Westerterp, K., and Heymsfield, S.B. 2012. Why do individuals

not lose more weight from an exercise intervention at a defined dose? An energy balance analysis. *Obesity Reviews* **13**(10): 835–847

Trudeau J. 2015. The Role of New Media on Teen Sexual Behaviors and Fertility Outcomes—the Case of ‘16 and Pregnant’. *Southern Economic Journal* **82**(3):975–1003.

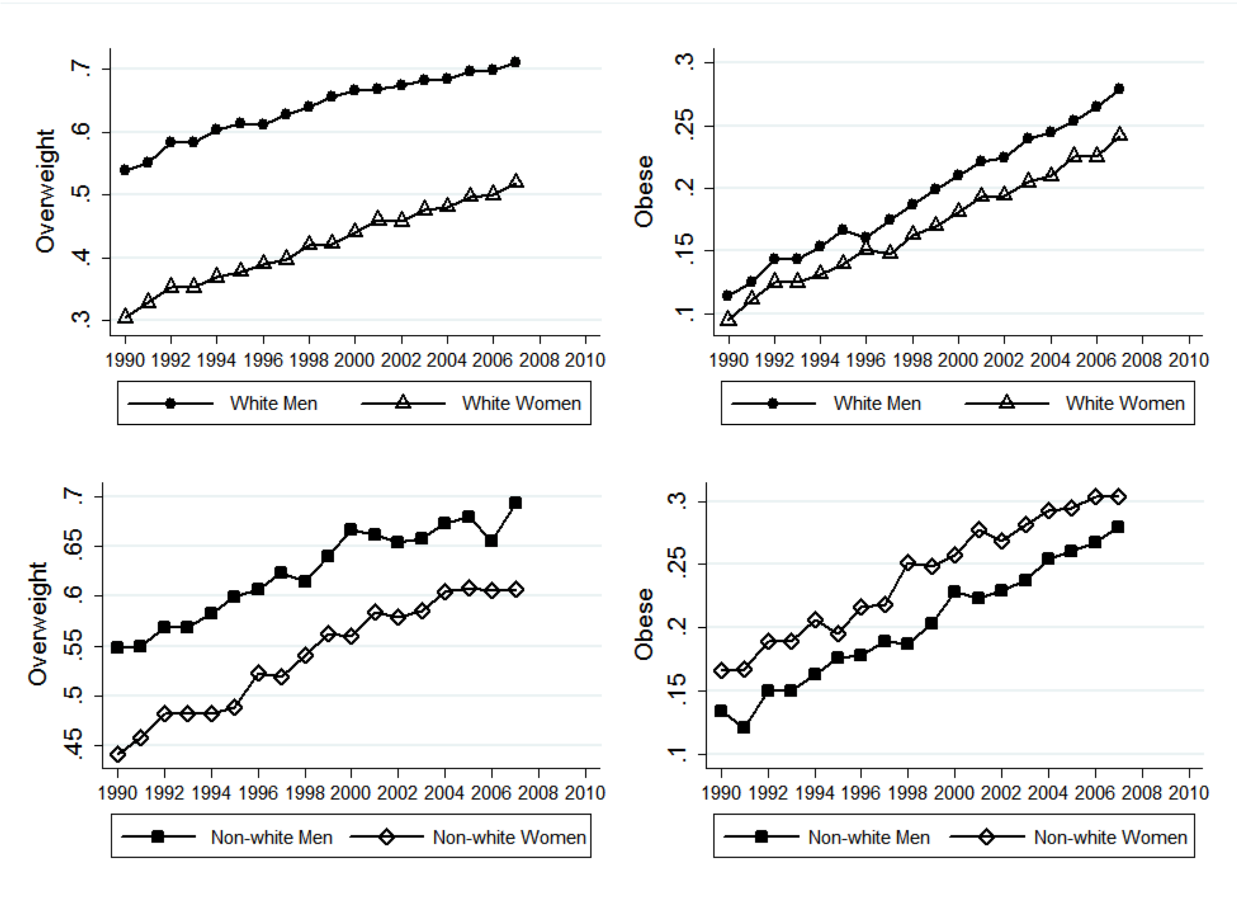
Wagner, T.H., Hu, T., and Hibbard, J.H. 2001. The Demand for Consumer Health Information. *Journal of Health Economics* **20**: 1059-1075.

Wellman, B. and Gulia, M. 1999. Net surfers don't ride alone: virtual community as community. In *Networks in the Global Village*, ed. Barry Wellman, pp. 331-67. Boulder, CO: Westview

Wellman, B., Haase, A. Q., Witte, J. and Hampton, K. 2001. Does the Internet increase, decrease or supplement social capital? *American Behavioral Scientist* **45**(3): 436–455.

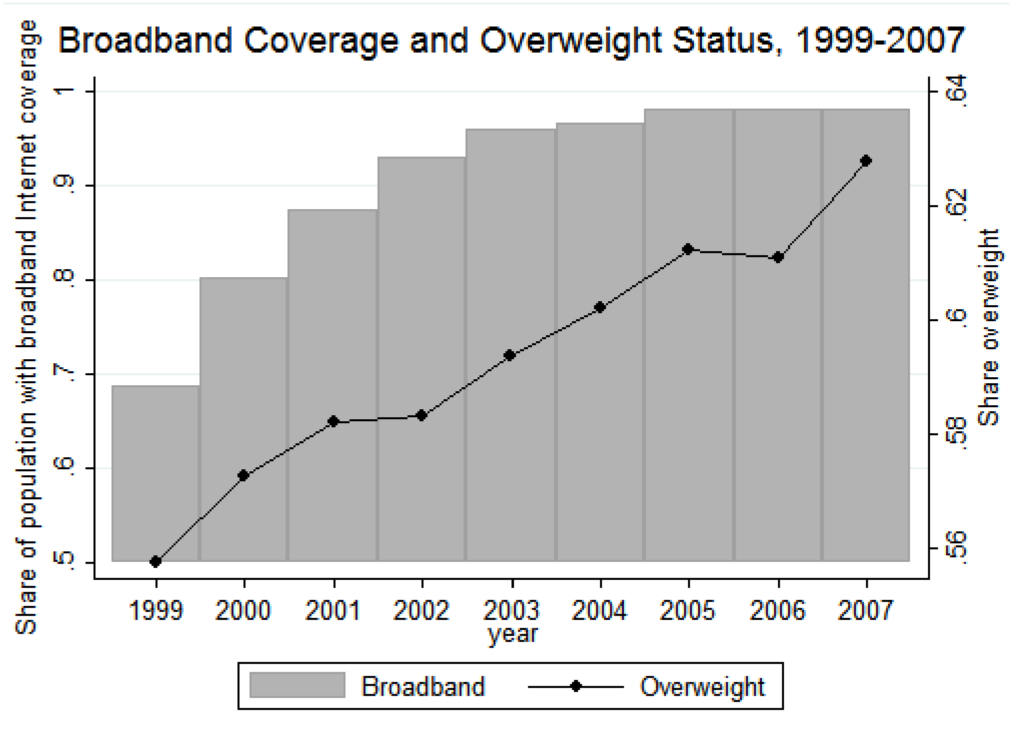
Zhao, S. 2006. Do Internet users have more social ties? A call for differentiated analyses of Internet use. *Journal of Computer-Mediated Communication* **11**(3): 844-862.

Figure 1: Trends in Fraction Obese and Overweight: 1990-2007



Source: Author's calculations using the 1990-2007 Behavioral Risk Factor Surveillance System surveys.

Figure 2: Broadband Coverage and Share Overweight: 1999-2007



Source: Author's calculations using the 1999-2007 Behavioral Risk Factor Surveillance System surveys and the 1999-2007 Federal Communications Commission Form 447 data.

Table 1: Summary statistics for full sample, 1999-2007

	Observations	Mean	Std. Dev.	Min	Max
Demographics					
Age	1,416,133	39.67	12.69	18	64
Female	1,416,133	0.490		0	1
Less than high school degree	1,416,133	0.099			
High school graduate	1,416,133	0.275		0	1
Some college	1,416,133	0.280		0	1
Bachelor's degree or higher	1,416,133	0.346		0	1
White	1,416,133	0.684		0	1
Black	1,416,133	0.109		0	1
Hispanic	1,416,133	0.146		0	1
Other race	1,416,133	0.062		0	1
Married	1,416,133	0.587		0	1
County-level covariates					
Broadband coverage	1,416,133	0.989	0.043	0	1
Unemployment rate	1,416,133	4.99	1.57	0.7	29.7
Real per capita income ($)	1,416,133	35,430	10,435	13,319	167,901
Weight					
BMI	1,416,133	26.85	5.66	4.78	99.98
Overweight (BMI $\geq$ 25)	1,416,133	0.589		0	1
Obese (BMI $\geq$ 30)	1,416,133	0.229		0	1
Behaviors					
Any exercise in last 30 days	1,340,457	0.782		0	1
Binge drinking event in last 30 days	1,406,907	0.628		0	1
Currently smokes	1,412,533	0.233		0	1

Note: BRFSS sampling weights used. Sample restricted to adults age 18-64. Observations from Louisiana omitted due to changes in infrastructure related to Hurricane Katrina. Observations from Virginia omitted due to an unusually large number of unmatched zip codes in FCC data.

Table 2: County-level socio-economic variables

	All	BRFSS	Non-BRFSS	p-value
Per capita income ($)	23,916.26	24,603.85	22,269.36	0.000
N:	3,110	2,194	916	
Unemployment rate	4.38	4.35	4.44	0.174
N:	3,139	2,195	944	
Urban	31.7	34.7	18.0	0.000
N:	2,606	2,129	477	
Total Population	288,764,448	271,189,824	17,574,624	
Mean Population	91,934	123,605	18,558	0.000
White (%)	84.4	85.1	82.9	0.001
Black (%)	8.9	8.4	10.2	0.002
Asian (%)	1.2	1.3	0.9	0.000
Other race (%)	2.9	2.9	3.0	0.973
N:	3,141	2,194	947	
<u>Education</u>				
Less than a high school diploma (%)	22.6	21.7	24.7	0.000
High school diploma (%)	34.7	34.4	35.2	0.002
Some college or associate's degree (%)	26.2	26.5	25.5	0.000
Bachelor's degree or higher (%)	16.5	17.4	14.6	0.000
N:	3,141	2,194	947	
<u>Social welfare expenditures ($1,000s)</u>				
Medicaid	70,455.63	93,884.80	14,338.16	0.000
N:	3,110	2,194	916	
Social Security Income	10,350.85	13,550.34	2,244.99	0.000
N:	3,060	2,194	866	
Earned Income Tax Credit	9,801.14	12,831.27	2,495.53	0.000
N:	3,104	2,194	910	
SNAP	4,833.13	6,152.47	1,310.62	0.000
N:	3,013	2,192	921	

Note: BRFSS counties are counties which appear in our BRFSS sample after being matched to our FCC data. Non-BRFSS counties are counties which do not appear in our BRFSS sample. All data is for the year 2000 except for the indicator for urban which is from 1993. The reported p-value is from a two-sided difference-in-means test between counties that appear in our sample and counties that do not. Per capita income and social welfare expenditure data from the U.S. Bureau of Economic Analysis. Unemployment rate is the average unemployment rate in 2000. Population, race, and education data from the U.S. 2000 Decennial Census. Education data is for county population age 25 and older. Urban is defined according to the 1993 Rural-Urban continuum codes provided by the U.S. Department of Agriculture.

Table 3: Estimates of the effect of broadband availability on weight, white samples

	Men				Women			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BMI	0.244	0.358	0.227	-0.205	1.026***	0.950**	0.853**	1.006**
	(0.268)	(0.250)	(0.249)	(0.348)	(0.365)	(0.358)	(0.353)	(0.461)
Mean:	27.3				25.9			
R^2	0.025	0.079	0.079		0.029	0.082	0.082	0.086
Overweight (BMI ≥ 25)	0.016	0.032	0.029	0.010	0.069**	0.064**	0.067**	0.065*
	(0.027)	(0.025)	(0.026)	(0.038)	(0.028)	(0.028)	(0.027)	(0.034)
Mean:	0.678				0.462			
R^2	0.018	0.082	0.082	0.087	0.024	0.074	0.074	0.077
Obese (BMI ≥ 30)	0.020	0.024	0.009	-0.024	0.061***	0.058***	0.048**	0.035
	(0.024)	(0.024)	(0.024)	(0.034)	(0.022)	(0.021)	(0.021)	(0.028)
Mean:	0.233				0.198			
R^2	0.021	0.042	0.042	0.047	0.022	0.050	0.050	0.050
Demographic controls		X	X	X		X	X	X
County controls			X	X			X	X
County linear time trends				X				X
N:	474,723	474,723	474,723	474,723	651,627	651,627	651,627	651,627

Note: Standard errors clustered at the county level. All regressions include month, year, and county fixed effects. Columns 2 and 6 add demographic controls: indicator variables for age, marital status, education (high school graduate, some college, and bachelor's degree or higher). Columns 3 and 7 add the county-level unemployment rate and county-level real per capita income. Columns 4 and 8 add county-specific linear time trends. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimates of the effect of broadband availability on weight, non-white samples

	Men				Women			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BMI	0.878	0.596	0.251	0.166	1.493*	1.419*	1.216	-0.051
	(0.798)	(0.723)	(0.689)	(1.015)	(0.776)	(0.737)	(0.750)	(1.089)
Mean:	27.33				27.37			
R^2	0.038	0.101	0.101	0.120	0.042	0.138	0.138	0.145
Overweight (BMI ≥ 25)	-0.033	-0.051	-0.092	-0.047	0.069	0.064	0.069	-0.038
	(0.073)	(0.065)	(0.067)	(0.102)	(0.069)	(0.068)	(0.068)	(0.082)
Mean:	0.664				0.585			
R^2	0.026	0.104	0.104	0.115	0.032	0.127	0.127	0.135
Obese (BMI ≥ 30)	-0.015	-0.026	-0.039	-0.006	0.088	0.082	0.068	0.062
	(0.068)	(0.067)	(0.064)	(0.092)	(0.060)	(0.057)	(0.054)	(0.082)
Mean:	0.241				0.277			
R^2	0.031	0.066	0.066	0.078	0.032	0.092	0.092	0.098
Demographic controls		X	X	X		X	X	X
County controls			X	X			X	X
County linear time trends				X				X
N:	111,669	111,669	111,669	111,669	178,114	178,114	178,114	178,114

Note: Standard errors clustered at the county level. All regressions include month, year, and county fixed effects. Columns 2 and 6 add demographic controls: indicator variables for age, race (Hispanic, all other races, black omitted), marital status, and education (high school graduate, some college, and bachelor's degree or higher). Columns 3 and 7 add the county-level unemployment rate and county-level real per capita income. Columns 4 and 8 add county-specific linear time trends. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Estimates of the effect of broadband availability on health behaviors, white samples

	Men				Women			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any exercise in last 30 days	0.089**	0.099***	0.099***	0.070	0.053	0.058	0.065*	0.148***
	(0.039)	(0.038)	(0.039)	(0.058)	(0.038)	(0.037)	(0.037)	(0.057)
Mean:	0.831				0.806			
R^2	0.028	0.078	0.078	0.084	0.031	0.078	0.078	0.082
N:	447,706	447,706	447,706	447,706	617,678	617,678	617,678	617,678
Any binge drinking events								
in last 30 days	0.105***	0.084***	0.073**	0.035	0.122***	0.120***	0.106***	0.063
	(0.029)	(0.029)	(0.028)	(0.044)	(0.037)	(0.037)	(0.036)	(0.047)
Mean:	0.619				0.575			
R^2	0.067	0.112	0.112	0.118	0.091	0.122	0.122	0.127
N:	470,818	470,818	470,818	470,818	649,059	649,059	649,059	649,059
Currently smokes	0.017	-0.007	-0.012	-0.012	0.041*	0.037*	0.031	-0.000
	(0.029)	(0.026)	(0.027)	(0.033)	(0.023)	(0.022)	(0.022)	(0.030)
Mean:	0.252				0.234			
R^2	0.024	0.116	0.116		0.022	0.117	0.117	0.118
N:	473,559	473,559	473,559	473,559	650,073	650,073	650,073	650,073
Demographic controls		X	X	X		X	X	X
County controls			X	X			X	X
County linear time trends				X				X

Note: Standard errors clustered at the county level. All regressions include month, year, and county fixed effects. Columns 2 and 6 add demographic controls: indicator variables for age, marital status, education (high school graduate, some college, and bachelor's degree or higher). Columns 3 and 7 add the county-level unemployment rate and county-level real per capita income. Columns 4 and 8 add county-specific linear time trends. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Estimates of the effect of broadband availability on health behaviors, non-white samples

	Men				Women			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any exercise in last 30 days	-0.108	-0.093	-0.094	-0.096	-0.020	-0.007	-0.027	0.023
	(0.084)	(0.082)	(0.085)	(0.068)	(0.065)	(0.066)	(0.071)	(0.103)
Mean:	0.734				0.669			
R^2	0.028	0.087	0.087	0.100	0.023	0.062	0.062	0.071
N:	105,574	105,574	105,574	105,574	169,435	169,435	169,435	169,435
Any binge drinking events in last 30 days	0.299***	0.293**	0.223**	0.282**	0.086	0.066	0.038	0.074
	(0.114)	(0.116)	(0.102)	(0.128)	(0.063)	(0.059)	(0.056)	(0.086)
Mean:	0.684				0.708			
R^2	0.053	0.077	0.078	0.091	0.048	0.078	0.079	0.087
N:	109,997	109,997	109,997	109,997	177,033	177,033	177,033	177,033
Currently smokes	-0.060	-0.091	-0.129*	-0.144*	0.025	0.014	0.021	0.090
	(0.081)	(0.077)	(0.075)	(0.087)	(0.056)	(0.053)	(0.055)	(0.060)
Mean:	0.254				0.165			
R^2	0.028	0.071	0.071	0.084	0.040	0.077	0.077	0.087
N:	111,259	111,259	111,259	111,259	177,642	177,642	177,642	177,642
Demographic controls		X	X	X		X	X	X
County controls			X	X			X	X
County linear time trends				X				X

Note: Standard errors clustered at the county level. All regressions include month, year, and county fixed effects. Columns 2 and 6 add demographic controls: indicator variables for age, race (Hispanic, all other races, black omitted), marital status, and education (high school graduate, some college, and bachelor's degree or higher). Columns 3 and 7 add the county-level unemployment rate and county-level real per capita income. Columns 4 and 8 add county-specific linear time trends. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Effect of broadband availability on exercise intensity, white samples

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Only moderate activity in a usual week	0.068	0.078	0.092	0.138*	0.142*	0.148*
	(0.069)	(0.073)	(0.074)	(0.082)	(0.082)	(0.041)
Mean						
R^2	0.022	0.054	0.054	0.020	0.043	0.043
N:	234,834	234,834	234,834	330,014	330,014	330,014
Only vigorous activity in a usual week	0.023	0.022	0.020	0.013	0.012	0.013
	(0.031)	(0.078)	(0.032)	(0.016)	(0.016)	(0.016)
Mean						
R^2	0.018	0.020	0.021	0.011	0.013	0.013
N:	234,834	234,834	234,834	330,014	330,014	330,014
Demographic controls		X	X		X	X
County controls			X			X

Note: Standard errors clustered at the county level. Moderate activity is defined as activity that causes small increases in breathing or heart rate. Vigorous activity is defined as activity that causes large increases in breathing or heart rate. These outcomes are only available in the following years: 2001, 2002, 2003, 2005, and 2007. All regressions include month, year, and county fixed effects. Columns 2 and 5 add demographic controls: indicator variables for age, marital status, education (high school graduate, some college, and bachelor's degree or higher). Columns 3 and 6 add the county-level unemployment rate and county-level real per capita income. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Effect of broadband availability on exercise intensity, non-white samples

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Only moderate activity in a usual week	0.142	0.138	0.137	-0.145	-0.128	-0.087
	(0.102)	(0.103)	(0.116)	(0.118)	(0.123)	(0.131)
Mean		0.276			0.432	
R^2	0.033	0.059	0.059	0.028	0.038	0.038
N:	53,218	53,218	53,218	87,850	87,850	87,850
Only vigorous activity in a usual week	0.089	0.085	0.060	0.093	0.091	0.098
	(0.100)	(0.097)	(0.106)	(0.068)	(0.067)	(0.066)
Mean		0.069			0.031	
R^2	0.033	0.042	0.042	0.025	0.029	0.029
N:	53,218	53,218	53,218	87,850	87,850	87,850
Demographic controls		X	X		X	X
County controls			X			X

Note: Standard errors clustered at the county level. Moderate activity is defined as activity that causes small increases in breathing or heart rate. Vigorous activity is defined as activity that causes large increases in breathing or heart rate. These outcomes are only available in the following years: 2001, 2002, 2003, 2005, and 2007. All regressions include month, year, and county fixed effects. Columns 2 and 5 add demographic controls: indicator variables for age, race (Hispanic, all other races, black omitted), marital status, and education (high school graduate, some college, and bachelor's degree or higher). Columns 3 and 6 add the county-level unemployment rate and county-level real per capita income. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Effect of broadband on weight interacted with county income indicators in 1999, white samples

	White Men						White Women					
VARIABLES	BMI		Overweight		Obese		BMI		Overweight		Obese	
Broadband	-0.040	0.212	-0.025	0.019	0.032	0.008	0.133	0.789*	0.009	0.061*	-0.003	0.063**
	(0.310)	(0.306)	(0.027)	(0.028)	(0.032)	(0.031)	(0.436)	(0.458)	(0.032)	(0.036)	(0.025)	(0.026)
Broadband x (Above median county income in 1999)	0.487		0.098**		-0.042		1.354**		0.108**		0.094**	
	(0.450)		(0.041)		(0.042)		(0.633)		(0.049)		(0.037)	
Broadband x (80th percentile county income in 1999)		0.412		0.076		0.016		1.153		0.086		0.009
		(0.606)		(0.0630		(0.050)		(0.781)		(0.060)		(0.051)
Broadband x (20th percentile county income in 1999)		-0.471		-0.043		-0.016		-1.054*		-0.070		-0.103**
		(0.481)		(0.048)		(0.041)		(0.631)		(0.048)		(0.042)
N:	474,723	474,723	474,723	474,723	474,723	474,723	651,627	651,627	651,627	651,627	651,627	651,627
R^2	0.079	0.079	0.082	0.082	0.042	0.042	0.082	0.082	0.074	0.074	0.050	0.050

Note: Standard errors clustered at the county level. All regressions include month, year, and county fixed effects. “Broadband x (80th percentile county income in 1999)” is an interaction between our broadband measure and an indicator for whether county is in the 80th percentile of county real per capita income in 1999. “Broadband x (20th percentile county income in 1999)” is an interaction between our broadband measure and an indicator for whether county is in the 20th percentile of county real per capita income in 1999. “Broadband x (Above median county income in 1999)” is an interaction between our broadband measure and whether county is above median county real per capita income in 1999. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Estimates of the effect of future (t+3) broadband availability on weight, white samples

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
BMI	0.390	0.399	0.305	-0.096	-0.058	-0.198
	(0.306)	(0.298)	(0.313)	(0.358)	(0.339)	(0.339)
R^2	0.02	0.079	0.079	0.025	0.082	0.082
Overweight (BMI ≥ 25)	0.024	0.027	0.033	-0.017	-0.013	-0.019
	(0.037)	(0.036)	(0.037)	(0.030)	(0.029)	(0.030)
R^2	0.016	0.080	0.080	0.020	0.073	0.073
Obese (BMI ≥ 30)	0.026	0.026	0.022	0.019	0.019	0.008
	(0.026)	(0.026)	(0.026)	(0.025)	(0.025)	(0.024)
R^2	0.015	0.038	0.038	0.017	0.044	0.044
Demographic controls		X	X		X	X
County controls			X			X
N:	340,242	340,242	340,242	440,138	440,138	440,138

Note: Standard errors clustered at the county level. We define "future broadband availability" as the level of broadband availability in a county three years from each year of the BRFSS sample, beginning in 1996. All regressions include month, year, and county fixed effects. Columns 2 and 5 add demographic controls: indicator variables for age, marital status, education (high school graduate, some college, and bachelor's degree or higher). Columns 3 and 6 add the county-level unemployment rate and county-level real per capita income. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Estimates of the effect of future (t+3) broadband availability on weight, non-white samples

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
BMI	1.608	1.309	0.600	0.710	0.675	0.256
	(1.113)	(0.974)	(0.977)	(0.742)	(0.66)	(0.697)
R^2	0.037	0.103	0.104	0.040	0.142	0.143
Overweight (BMI ≥ 25)	0.194	0.170	0.105	0.071	0.072	0.041
	(0.121)	(0.107)	(0.109)	(0.076)	(0.072)	(0.071)
R^2	0.024	0.100	0.100	0.031	0.130	0.130
Obese (BMI ≥ 30)	0.024	0.009	-0.026	0.008	0.001	-0.016
	(0.065)	(0.059)	(0.061)	(0.059)	(0.059)	(0.062)
R^2	0.026	0.058	0.058	0.029	0.086	0.086
Demographic controls		X	X		X	X
County controls			X			X
N:	81,445	81,445	81,445	120,588	120,588	120,588

Note: Standard errors clustered at the county level. We define "future broadband availability" as the level of broadband availability in a county three years from each year of the BRFSS sample, beginning in 1996. All regressions include month, year, and county fixed effects. Columns 2 and 5 add demographic controls: indicator variables for age, race (Hispanic, all other races, black omitted), marital status, and education (high school graduate, some college, and bachelor's degree or higher). Columns 3 and 6 add the county-level unemployment rate and county-level real per capita income. All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A1: Effect of broadband on weight using "balanced counties" samples

	Men		Women	
	White	Non-white	White	Non-white
BMI	0.395	0.079	1.222***	1.503
	(0.289)	(1.061)	(0.433)	(1.283)
R^2	0.072	0.093	0.077	0.132
Overweight (BMI ≥ 25)	0.031	-0.172*	0.099***	0.108
	(0.030)	(0.102)	(0.034)	(0.118)
R^2	0.076	0.099	0.069	0.125
Obese (BMI ≥ 30)	0.021	-0.054	0.075***	0.091
	(0.028)	(0.103)	(0.026)	(0.091)
R^2	0.035	0.058	0.044	0.084
N:	365,921	85,766	496,779	136,261

Note: Standard errors clustered at the county level. Each sample only includes observations from counties that are in the BRFSS every year in our sample period. All regressions include indicator variables for age, marital status, education (high school graduate, some college, and bachelor's degree or higher), county-level unemployment rate and county-level real per capita income, month fixed effects, year fixed effects, and county fixed effects. Regressions for the non-white samples also include indicators for Hispanic and other race (black race omitted). All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Effect of broadband on weight, monthly fixed effects specifications

	Men		Women	
	White	Non-white	White	Non-white
BMI	0.212	0.204	0.855**	1.245*
	(0.249)	(0.680)	(0.351)	(0.744)
R^2	0.080	0.104	0.082	0.140
Overweight (BMI ≥ 25)	0.028	-0.091	0.066**	0.069
	(0.026)	(0.067)	(0.027)	(0.068)
R^2	0.083	0.107	0.074	0.129
Obese (BMI ≥ 30)	0.009	-0.046	0.048**	0.071
	(0.024)	(0.064)	(0.021)	(0.053)
R^2	0.043	0.069	0.050	0.093
N:	474,723	111,669	651,627	178,114

Note: Standard errors clustered at the county level. All regressions include indicator variables for age, marital status, education (high school graduate, some college, and bachelor's degree or higher), county-level unemployment rate and county-level real per capita income, month of year fixed effects (e.g. January 1999), and county fixed effects. Regressions for the non-white samples also include indicators for Hispanic and other race (black race omitted). All regressions are weighted using the BRFSS sampling weights. *** p<0.01, ** p<0.05, * p<0.1