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Exploring the Relationship Between Broadband and Socioeconomic Health: A Case Study in Appalachia

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EXPLORING THE RELATIONSHIP BETWEEN BROADBAND AND SOCIOECONOMIC HEALTH: A CASE STUDY IN APPALACHIA

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ABSTRACT

This thesis uses county-level Federal Communications Commission (FCC) Form 477 and Appalachian Regional Commission data to examine factors that affect socioeconomic health, with a particular focus on the impact of household broadband adoption, in rural areas of the Appalachian United States. Outcome variables of interest are percentage of people in poverty, per capita market income (i.e., the income one earns from participating in the economy through wages, investments, business income and the like), and number of excess deaths per 100,000 residents. The first chapter uses two multivariate multiple regression models, one using 2008 data and one using 2016 data, to assess the impact of household fixed broadband connections per thousand residents, education (as measured by high school graduation rate), unemployment rate, and county economic dependency, on income and percent of people under the poverty line in two time periods.

The second chapter uses an Ordinary Least Square (OLS) regression to evaluate the relationship between rurality and excess mortality when socioeconomic variables, including broadband adoption, percent of adults with high school degrees, unemployment rate, percent of people in poverty, per capita market income, and county economic dependency, are controlled for. The results for the first two models depict a statistically significant and negative association between low levels of broadband adoption and income in counties, and a statistically significant negative association between low levels of broadband and percent of people in poverty in 2016. There was no significant association between broadband and excess mortality, but these results do suggest that socioeconomic factors play a larger role in contributing to excess mortality than whether a county is rural or urban. In particular, transfer payments (i.e., government aid) were positively and significantly associated with higher levels of excess mortality. Establishing causality remains

an important consideration when assessing policy aimed at improving rural quality of life through increased broadband availability and adoption, and should be a central influence on policy and funding decisions going forward. Improving data quality and accuracy should also be a priority going forward, as this is necessary for determining whether funding programs are producing tangible benefits.

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1. CHAPTER I: INTRODUCTION

Nearly every aspect of modern life is informed and impacted by the availability of internet access - or lack thereof. For example, remote connectivity is a crucial aspect of work (Pratt 2002), education (Davidson and Santorelli 2010), healthcare (Perkins 2018), and disaster preparedness (Tremaine and Tuberson 2017, Gruntfest and Weber 1998). Digital technologies today enable individuals to attend classes and do homework online, work remotely, videoconference with doctors, and do research on their diagnoses. Real-time weather tracking and emergency communication allow people to be notified of disasters both natural and man-made. Consumers can shop online for products ranging from books to electronics to groceries. Online shopping as a percent of total retail sales has steadily increased over the past decade rising to an all-time high of 11.8% for Q4 2019. The effects of the Covid-19 pandemic further increased that number to 16.1% for Q2 2020 (Census Bureau 2020).

The importance of internet connectivity is underscored in rural areas, where spatial dispersion of people may mean that brick-and-mortar facilities are not easily accessible. A small town may not be able to support its own doctor's office or immediate care facility, but telehealth enables individuals to seek medical care from far away. An individual without reliable personal transportation, living in an area where public transportation is unavailable or unreliable, may have difficulty finding gainful employment. Internet access can enable this person to work remotely, even in areas such as customer service (Stenberg et al. 2009).

The share of the U.S. population that uses the Internet has increased steadily over the past two decades. Currently only 10% of adults say they do not use the Internet at all (Pew Research, 2019). However, a 2016 Council of Economic Advisers report indicated that 24.2% of American households did not access the Internet from home in 2014, according to Census data from the

American Community Survey (CEA, 2016). A possible explanation for this discrepancy is that some individuals use the Internet, but do not have a home connection: instead, they access the Internet at work, school, or public places such as coffee shops and libraries.

Additionally, adoption has been uneven across demographic groups, as 27% of respondents over the age of 65 and 45% of respondents with a high school diploma or less say they are not online (Pew, 2019). Patterns of subscribership tend to follow racial, educational, and financial lines. Per the CEA report (2016), income, educational attainment and broadband subscription are positively associated,. For example, individuals with a bachelor's degree or higher are the more likely to have internet at home (90.9%). This percentage declines substantially down the educational ladder to those with less than a high school diploma (46%). Regarding ethnicity, Asian households (87.6%) and Caucasian households (77.6%) are the demographic segments for whom greater than three-quarters of households had subscribed (CEA 2016).

In terms of geographical distribution, Dickes et al. (2009) reported that the Northeast and Western U.S. regions had higher adoption rates compared to the Midwest and South. Moreover, Appalachia and the Deep South[1] continue to lag behind the rest of U.S. (CEA, 2016). This discrepancy between internet adoption in rural and urban areas may be explained by patterns of poverty - which often persist among Americans in rural communities in the South, and Appalachia, particularly among Caucasians.

From an availability perspective, according to the 2016 Broadband Progress Report, 10% of Americans - including 39% of rural Americans and 4% of urban Americans - did not have access to internet service at speeds of 25mbps downstream and 3mbps upstream, which is the Federal Communications Commission's threshold to be considered served.

[1]A cultural region which generally refers to cotton-growing states, most often includes LA, AL, and MS

The issue of low internet adoption among certain demographic groups (adults with lower education, residents of rural areas etc.) is multifaceted: Even when service is available, many people choose not to subscribe for reasons of cost, lack of ownership of a personal computer, or a perception of the internet as dangerous or irrelevant. Some individuals choose not to subscribe because they can access the internet in public places such as libraries or coffee shops, although this alternative is more difficult to rely upon in very rural areas (Horrigan 2010).

Closing this 'digital divide' has been a political talking point for the past several administrations. Early efforts to promote broadband infrastructure focused on providing funding, in both grant and loan form, to communities and potential investors. In 2000, Congress directed the Rural Utilities Service (RUS) of the USDA to create and enact a pilot loan and grant program for the express purpose of furthering broadband deployment in rural communities. The USDA, a longtime provider of home and business loans to disadvantaged communities, issued the first round of broadband loans in FY2002. Since FY2004, , the RUS has approved a total of "704 broadband projects totaling $8.6 billion in loans and $144.8 million in grants" (GAO 2017).

The 2009 stimulus package put forth by the Obama administration earmarked $7.2 billion for broadband expansion, and by the end of 2011, more than 45,000 network miles had been deployed (Eisenach & Caves 2011). However, these results have been subject to criticism from scholars who argue that the cost of providing this "last mile" of service far outweigh any perceived benefit (Eisenach & Caves 2011).

More recently, Sonny Perdue (Secretary of Agriculture) invoked broadband as the backbone of his recommendations in the 2017 "Report to the President of the United States from the Task Force on Agriculture and Rural Prosperity" (USDA, 2017). The briefing featured five overarching "calls to action", which addressed topics such as quality of life, workforce and economic development, and technological advancement. His recommendations included reviewing and revising existing regulations “to encourage investment in reliable, high-speed internet in rural areas, expedite approval and internal review timelines and streamline permitting processes to promote increased build-out of infrastructure”, and, correspondingly, incentivizing private investment in broadband deployment.

Currently, the RUS maintains four programs aimed at advancing rural broadband technology: i) Rural Broadband Access Loans, which are used to fund the acquisition and management of facilities and equipment; ii) Community Connect Grants, which are used to fund deployment into areas where “it is not yet economically viable” for private providers to extend service; iii) Telecommunications Infrastructure Loans and Loan Guarantees, which fund telephone and broadband service in communities of 5,000 people or less; and iv) Distance Learning and Telemedicine Grants, which are used to connect rural communities with educators and medical providers remotely. In 2018, the RUS received $600 million in appropriated funds to create a new broadband loan and grant program with additional stipulations, including a condition that at least 90% of the households in the communities served by the grants be considered rural and without access to broadband (CRS 2018). These new guidelines are likely in response to past criticisms that broadband loan and grant funds were often awarded to metro-adjacent communities that were not truly rural, or to communities that already had an existing broadband provider.

Given the enormous outlay of funds (as detailed above, $8.6 billion as of 2016; another $600 million approved in 2018) into furthering broadband expansion, particularly over the past three presidential administrations, there is great interest into whether any tangible gains to rural America have been realized thus far. Proponents of government funding for broadband expansion often cite the Great Depression-era Rural Electrification Act, which is widely believed to have had a highly positive impact on rural prosperity during a difficult economic time and at a low cost to taxpayers because loans were mostly repaid (Kitchens and Fishback 2013). Critics, by contrast, point out that government outlays on broadband may be greater than the economic value of broadband to a community and that government allocation of funds is often wasteful and inefficient (Eisenach and Caves 2011).

The second chapter of this thesis evaluates the impact of broadband adoption on socioeconomic health, as measured by (1) per capita market income[2] and (2) percentage of people in poverty, in the Appalachian United States with a focus on rural areas. The mountainous geography of many areas within the Appalachian region has presented a challenge to expanding broadband access there, and the region has historically struggled with high levels of poverty, substance abuse, and other social and economic struggles. This has been particularly true in recent years as key industries in the region, particularly coal mining in central Appalachia, have diminished. The third chapter of the thesis evaluates the relationship between broadband and excess mortality rates using the same set of explanatory variables as in chapter 2, which are broadband score, percent of adults with a high school diploma, unemployment rate, rural classication, and county economic dependency, as well as market income, poverty, and transfer payments per capita.

The contribution of this thesis is twofold: first, previous studies on broadband's impact on socioeconomic outcomes have focused on all counties or Census tracts within a state or states. In contrast, this thesis will examine the impact of broadband counties across state lines, within a common and distinct economic and cultural region: Appalachia. The mountainous regions of western Virginia, for example, may be quite different from the urban, coastal areas.

Second, while it is well documented that rural areas experience higher levels of excess or avoidable deaths, there has been comparatively less research into whether this problem is intrinsic

[2]Defined more precisely in the next chapter, market income is the income that indivuals earn from participating in the economy, i.e. from non-governmental sources

to rural areas or is co-occurring with other social ills such as poverty, drug use, and teen pregnancy. This thesis will seek to more precisely define why rural communities often experience higher levels of excess mortality, taking other socioeconomic factors into account, such as unemployment rate, poverty, and income.

The second chapter of the thesis constructs two multivariate multiple regression models using county-level data from two points in time from the Federal Communications Commission (FCC)'s Form 477[3], which maintains semi-annual data on the number of fixed Internet connections in a given area, as well as economic and demographic data from the Appalachian Regional Commission (ARC). The dataset contains information on 420 counties across thirteen states the ARC has identified as part of the region, for the years 2008 and 2016. The third chapter of the thesis applies an ordinary least squares (OLS) regression using the same data from 2016, as well as data on excess deaths from the CDC WONDER database.

Chapter 2 consists of three major sections. Section 2.1 presents an overview of existing literature on broadband diffusion and adoption and its economic impacts. Section 2.2 explains the sources of the data and provides commentary on its scope, and details the statistical methodology for the multivariate multiple regression models. Section 2.3 presents the results of the first two equations, which find a statistically significant and negative association between low levels of broadband adoption and market income, and a statistically significant positive association between low levels of broadband and poverty only in 2016. Chapter 3 presents a supplemental analysis of excess mortality in rural versus urban areas, and finds that differences in excess mortality can be largely attributed to differences in economic status. Chapter 4 concludes and provides a discussion on further research considerations, as well as discusses policy recommendations.

[3] Form 477 is a reporting requirement that the Federal Communications Commission imposes on broadband providers on a semiannual basis. It is discussed in greater detail in the following section.

2. CHAPTER II: BROADBAND'S EFFECT ON POVERTY AND INCOME

2.1 LITERATURE REVIEW

Literature on the economic impact of broadband can generally be categorized into two overarching areas: (1) factors which incentivize individuals to subscribe to broadband, and (2) the extent to which the presence of broadband impacts the local economy. Within the latter, the research makes a clear and important distinction between broadband *availability* in a given geographic area and broadband *adoption* among the population in that area. Highlighting the relative importance of availability versus adoption can help policymakers and activists understand which area of focus is most important to promoting rural prosperity.

What Incentivizes Adoption?

Glass and Stefanova (2010) assessed the factors that affect broadband access and adoption decisions in rural communities in the U.S. They used a two-equation approach that modeled rural companies' decision to offer broadband service (an offer equation) and rural customers' decision of whether or not to subscribe (a take rate equation) using cross-sectional data from the FCC's Form 477 and the National Exchange Carrier Association (NECA) from 2005 and 2009. Their results indicate that larger average loop lengths - the amount of cable required to deploy service - and a smaller proportion of people with a telephone decreased the probability that the company would offer DSL service. On the consumer side, they found that advertised speed was positive and significant in 2005, but was negative and not statistically significant in 2009. They found that price elasticity of demand was lower in 2009 than 2005, which they interpreted as an indicator that broadband had become more of a necessity during that time period. This finding among current subscribers is an important distinction from Horrigan

(2010), who conducted a survey of potential consumers for the FCC and found that cost of service is a major factor in the decision to subscribe. The same survey also cited a perception of the internet as irrelevant or dangerous among non-users, in addition to a lack of computer access and difficulty using technology, as reasons for non-adoption.

By contrast, Glass and Stefanova (2010) found that price and speed alone do not affect demand but the availability of advanced services, such as video streaming and other types of multimedia, do play a role in increasing demand. They conclude with a warning that government policy aimed at broadband deployment should seek to reduce costs of certain types of services – particularly multimedia – to spur adoption, rather than merely focusing on infrastructure development.

Similarly, Whitacre et al. (2013) evaluated a subset of the results of a grassroots program called Connected Nation, which maps broadband availability and works with providers and community leaders to encourage adoption. They used county-level Form 477 data from 2008 (the earliest available) to 2011 (so as to have both pre- and post-adoption data). Of the thirteen states that participated in the program, two states – Ohio and Tennessee – participated between 2008 and 2011, the time period of interest. The authors compared outcomes of participating counties with non-participating counties using 2008 levels of various socioeconomic and demographic metrics and found that participating in Connected Nation had a strong positive impact on infrastructure development (the number of providers in a given area), especially for the most rural counties, but increased availability did not lead to increased household broadband adoption, particularly in the most rural counties. A more recent study by Manlove and Whitacre (2018), however, found that participants may experience a positive effect on adoption beginning four years after program participation. This suggests that it may take time for the ripple effects of broadband availability - and perhaps adoption - to be truly felt by rural communities.

Does Adoption Impact the Economy?

Broadband's economic benefits to individuals can manifest in several ways. Access to broadband can have a direct impact on the number of businesses and number of jobs in an area (Crandall et al. 2007, Shideler et al. 2007) , which can then trigger secondary improvements in metrics such as median household income, unemployment rate, and education level, among others (Whitacre et al. 2014).

Even when and where levels of household adoption are low, individuals may benefit when companies for whom broadband is a necessity are now able to locate in areas where broadband is available – thus creating jobs. Kim and Orazam (2016), examining firm location choice in Iowa and NC, found that availability of broadband increased the probability that a new firm chose to locate in a given ZIP code from 0.10% to 0.17%[4]. They used a difference-in-differences model to measure the location-choice probability of firms in the early 1990s, before broadband was available at all, and compare that with the location-choice probability of firms in the early 2000s.

While Kim and Orazem (2016) analyzed firm location choice, for which number of jobs is a secondary measure, Crandall et al. (2007) looked directly at employment numbers by industry. They used a multivariate multiple regression model that regressed private nonfarm employment and gross domestic product on broadband lines per capita and several predictor variables, including state mean annual temperature, business tax climate index, percent of employees in unions, average hourly earnings, share of adults who are college graduates, and a set of nine regional dummy variables. They found that non-farm employment between 2003 and 2005 was positively associated with broadband adoption: for every one percentage point increase

[4] Although this seems like a small change in probability at first glance, NC and IA have a combined total of over 1,850 zip codes. The probability of any given zip code being chosen for firm location is therefore very small to begin with.

in broadband use, employment was projected to increase by 0.2 to 0.3 percent. The sectors whose employment was most impacted by broadband adoption were education, healthcare, and financial services, which conformed to their expectation: to the extent that Internet access can help to mobilize a rural workforce, broadband is likely to have the strongest impact on service-sector occupations. Contrary to their expectations, they also found that broadband had a positive impact on employment in manufacturing, but not in real estate. Real estate was one of only two industries in which broadband adoption had a statistically significant effect on output (measured by GDP) in the 2004-2005 period.

Similarly, Shideler et al. (2007) used county business patterns data to examine the effects of broadband availability on employment economy-wide and by industry in Kentucky from 2003-2005. They used a multivariate stepwise regression with overall employment growth rate and employment growth rate in each of the 21 two-digit industrial classification (NAICS) codes in the 2004-2005 period as the dependent variable outcomes of interest. Their independent variables included a broadband variable, the percent of people age 25 and over with a bachelor's degree, the number of limited-access highway miles (as a proxy for infrastructure), unemployment rate, and a binary dummy for whether the county was metro or nonmetro.

As opposed to using Form 477 data, which measures adoption, the researchers measured broadband availability by using geographic information system (GIS) data obtained through ConnectKentucky, another Connected Nation participant. They computed a "saturation rate" (in percentage) using a ratio of area covered by broadband to total area as of January 2004 (p. 93). For example, if a county's total area is 50 square miles and broadband is available in 30, the saturation rate would be 0.6, or 60%. They also computed a saturation rate squared to capture the effect of returns to scale.

The overall R^2 of their model improved, notably, to 0.096 in the model with all the variables included from 0.008 in the identical model without broadband. Economy-wide, the coefficients on broadband market saturation and saturation rate squared were positive and highly significant. No other predictor variables were statistically significant.

They subsequently replicated the estimation for all 21 NAICS classifications and found that broadband availability had a positive impact on employment growth in several industries, including information technology, administrative, support, waste management services, and mining. The effect was statistically significant in the industries of real estate, arts, entertainment, and recreation, and unclassified industries in the initial model, but the effect was statistically insignificant when other control variables were added to the model. In contrast to Crandall et al. (2007), Shideler et al. (2007) found that broadband did not have a statistically significant impact on employment in the healthcare industry, which they attribute to low industry adoption rates at that time. Notably, because Shideler et al. (2007) used data from a single state whereas Crandall et al. (2007) used nationwide data, it may be that the impact of broadband on a particular industry is asymmetric across states depending on the strength of that industry within a particular state.

Broadband had a negative and significant impact on employment growth in the accommodations and food services industries, suggesting that Internet connectivity may enable individuals to search online for services they would otherwise obtain from local providers. Economic theory suggests broadband may have an ambiguous effect on retail establishments in rural areas(Whitacre et al. 2014). Rural companies can reach a more wider audience by selling their products online - whether through their own websites or through cloud-hosted business platforms such as eBay and Etsy - but e-commerce can also enable rural consumers to purchase goods and services online rather through local sellers. The same may be true for financial and professional services, where rural consumers can outsource their business rather than partaking of professionals in local markets (Whitacre et al. 2014).

More recently, Mack (2013) used a spatial model to assess the relationship between broadband speed and firm location, as measured by number of establishments, in Ohio in 2010. She found that broadband speed was had a statistically significant impact on the number of firms for "all establishments" (i.e., without differentiating by sector), agricultural establishments, and rural establishments. However, other industrial sectors such as retail, healthcare, and knowledge work did not experience similar benefits. She attributed this unexpected result to i) the inadequacy of using a residential proxy for broadband, which would not fully capture the use of privately leased lines, and, importantly, ii) that the FCC's speed threshod may not be high enough to make a difference for firm location selection.

Similar to Glass and Stefanova (2010), Whitacre et al. (2014) used a cross-sectional model and a panel model to assess whether availability and adoption of broadband affected several important measures of rural economic health: number of business establishments, median household income, and percentage of nonfarm self-employed. They used county-level Form 477 data from 2008 – 2011 and broadband availability data from the National Broadband Map, an FCC endeavor which has since been discontinued. Their models featured a set of 18 explanatory variables, including categorical variables for age, race, and education level, as well as unemployment rate, ranking on natural amenities scale, and dummies for whether the county was non-metropolitan, micropolitan, or non-core. Their analysis interacted broadband variables with a non-metropolitan variable to measure the difference between the general impact of broadband and its specific impact in rural counties; that is to say, their data included both metro and nonmetro counties, and their results were estimated for micropolitan and noncore counties.

They found that availability of broadband has no impact on income levels and employment, but that non-metro counties with residential *adoption* rates of greater than 60% do have more businesses and more total employees. They also found a positive impact of increases in broadband adoption between 2008-2011 on median household income growth in rural counties over the same period. They note that high broadband adoption levels in 2011 are *not* associated with income levels in their cross-sectional analysis, but *changes* in each of the variables over the three-year period are. When they replicated the regressions using number of providers (an availability measure) rather than changes in adoption, the results were not statistically significant. Consistent with previous literature, these results further suggest that adoption and subscribership are more important than simply the availability of the technology.

Whitacre et al.(2013) found that rural counties with adoption rates of over 60% experienced significantly higher levels of growth in median household income and significantly lower levels of unemployment compared to similar counties that did not have 60% adoption. Availability alone had little to no impact on the economic indicators they measured. They agree with Crandall et al. (2007) and Glass and Stefanova (2010), that efforts should concentrate on furthering broadband *adoption*, because simply increasing availability may not have the desired effect.

Metro adjacency is another important consideration in the literature. Kim and Orazem (2016) note that rural counties adjacent to metropolitan counties (RUCC 6) are the most likely to gain firm entry from local broadband availability, with a proportional gain in probability of 83%, while the least populated, most remote counties (RUCC 9) have the smallest gain from broadband availability (proportional gain of entry of 51%), during the period of interest from 2008-2011 (Kim and Orazem 2016).

They remark that the effect of broadband is most strongly felt in the presence of agglomeration economies, which are often found in counties closer - if not adjacent - to metro areas. Using a difference-in-differences fixed effects model, Kandilov and Renkow (2009) evaluated the effects of early-stage participation in the USDA's Broadband Loan program using zip-code level data and compared communities that received a broadband loan (the treatment group) with communities that did not. They found that recipient communities experienced a "substantial positive impact on employment, annual payroll, and the number of business establishments" as a result of the program, but, like Kim and Orazem (2016), noted that the outcomes were almost exclusively felt in communities close to urban centers. Similarly, a 2016 report from the Hudson Institute estimating the direct and indirect effects of rural broadband found that only 34% of the final economic benefit from rural telecommunications was realized by rural areas, with the remaining 66% accruing to urban areas (Hudson Institute, 2016).

This reflects a formidable problem. Rural broadband is often championed as a key to economic growth for remote, sparsely populated, often economically depressed communities ("Rural America will fall further behind without all-fiber broadband infrastructure investment", "We Need a National Rural Broadband Plan"). To the extent that metro-adjacent counties are reaping the benefits of broadband more than truly rural counties, the broadband initiative is not having the desired effect - rather, the result "contrasts markedly with the stated objective of these programs of promoting economic development in rural areas" (Kandilov and Renkow 2009). In other words, the areas in greatest need of a force to spur economic development are the areas in which the potential benefits of broadband are generally not as fully realized. This is of great concern from a cost-benefit perspective, as Kim and Orazem (2016) note, because building out end-user infrastructure - "the last mile" - is more challenging and more costly from an absolute perspective in rural areas, particularly those in mountainous regions.

Further, because each "last mile" of infrastructure reaches fewer individuals in rural areas than in metro areas, the per capita cost is also higher, which implies a higher threshold of revenue is necessary to recoup the costs. The government can (and, through the Broadband Loan program, has attempted to) offset these costs, but the aforementioned research calls into question whether the net benefit of universal broadband access is positive - particularly in light of earlier findings that adoption plays a bigger role than availability in promoting the economic health of rural communities. Understanding demand for broadband is crucial here, as Horrigan's 2010 survey found that only 4% of non-users[5] cited unavailability in their area as the *primary* reason for their lack of home internet, even as the FCC's 2016 report states that 39% of Americans in rural areas were, at that time, without access to 25 Mbps upstream/3 Mbps downstream, a relatively low threshold of speed (FCC 2016). This contrast harkens back to the availability/adoption paradigm and the results of the Connected Nation program discussed in Whitacre et al. (2013): building infrastructure is one piece of the broadband puzzle, but incentivizing adoption is entirely different.

Existing literature on broadband adoption has mostly used either difference-in-differences or multivariate regression to assess broadband's impact on the local economy. This thesis draws upon previous methodologies - specifically, multivariate multiple regression with panel data - in attempt to replicate and expand upon earlier findings by Whitacre et al. (2014) on the relationship of broadband to selected measures of socioeconomic health for a defined geographic area. Like previous studies, this thesis uses county-level data from two time periods spaced several years apart (2008, the earliest year for which Form 477 broadband data is currently available, and 2016, the latest year for which socioeconomic data on all variables of interest is available from the Appalachian Regional Commission). Rather than focus on the number of

[5] 5,005 survey respondents; 2,334 were non-adopters

establishments or total number of people employed, this thesis uses market income per capita and percentage of people in poverty as outcome variables of interest in this chapter, and excess mortality as the outcome variable of interest in the third chapter. Finally, the scope of this thesis focuses on 420 counties across 13 states in the Appalachian mountain region of the United States, which is a cultural region that has historically suffered from high levels of poverty, unemployment, and substance abuse, and is an area where the potential impact of broadband adoption has not been extensively studied.

2.2 DATA AND METHODS

Broadband Adoption Data

Broadband adoption data on a county level for December 2008 and December 2016 were obtained from the FCC Form 477[6]. All broadband providers are required to disclose to the FCC on a semiannual basis all of the geographic areas in which they provide fixed internet service at "speeds exceeding 200kbps in at least one direction" (Fixed Broadband Deployment Data from FCC Form 477). The FCC then produces county-level and Census tract-level datasets for every county and Census tract in the United States. These datasets report several metrics related to broadband availability (as measured by number of providers) and adoption (as measured by the number of fixed connections). At this writing, the earliest available county-level dataset was effective December 31, 2008, and the latest available dataset was effective December 31, 2018.

Over the years, the FCC's reporting methodology has undergone several changes. From 2008 until 2014, the FCC reported: i) the number of residential fixed connections over 200kbps in at least one direction (either upstream or downstream) per 1,000 households, ii) the number of

[6] Accessed October 12, 2020

residential fixed connections over 3mbps downstream and 768kbps upstream per 1,000 households, iii) the number of providers of each type, and iv) the number of mobile providers.

In 2014, the FCC dropped its data on the number of providers and reported only residential adoption metrics, and in 2015, changed the highest-speed threshold from 3mbps downstream and 768kbps upstream to 10mbps and 1mbps, respectively. Finally, as of June 2016, the FCC changed its reporting structure for that release to a single threshold, the original 200kbps in any direction; disaggregated the number of connections into residential and non-residential, and now reports the total number of connections (in thousands). From 2008 to 2015, adoption data were reported on a per-1000-household basis and the results aggregated into six groups. To enable consistency with the 2008 data, the 2016 connection data were reclassified into groupings consistent with those previously used by the FCC. The FCC's county classification grouping thresholds, and the buckets for this analysis, are reported in Table 2.1.

Table 2.1 FCC Broadband Classification Scores – Per Thousand Households

Classification Score	# Fixed Broadband Connections per 1000 Households
0	0
1	1 – 200
2	201 – 400
3	401 – 600
4	601 – 800
5	> 800

To enable consistency across time, broadband adoption was measured using the 200kbps threshold in the FCC's original interval estimation on a yearly basis. Two years of data were used: December 2008 and December 2016, as 2016 was the most recent year for which data for all socioeconomic variables of interest could be obtained from the ARC.

Table 2.2 depicts the distribution of broadband scores across ARC counties in the years 2008 and 2016. Notable is the upward shift in the distribution across the five categories. While in 2008 the bulk of Appalachian counties had 60% adoption or less, in 2016 most counties had greater than 60% adoption. This depicts an overall increase in the share of households subscribing to broadband at home, and reflects a general trend toward the increasing importance of Internet connectivity in American life as more and more activities benefit from or require Internet access.

Table 2.2: Tabulation of Broadband Classification Score by Year for ARC Counties

Broadband Score	2008	2016	Percent Change
1	25	0	-100%
2	174	10	-94%
3	173	100	-42%
4	41	238	+480%
5	7	54	+671%
Total	420	402[7]	

Economic Data

The primary source of socioeconomic data in this paper is the Appalachian Regional Commission (ARC), which is a governmental partnership between the federal government and the state governments of the 13 states which have territory in the areas in and around the Appalachian mountains in the eastern United States. The ARC has identified 420 counties it classifies as part of this region, which is the basis for this analysis. A map of this region can be found in Appendix I.

As part of its work, the ARC maintains a repository of data on these counties compiled from multiple federal sources, including the Census Bureau, Bureau of Labor Statistics, and the Department of Commerce. These data are used to rank and classify counties based on their socioeconomic health. The data of interest in this chapter are: unemployment rate, percentage of people in poverty (i.e., below the federal poverty line), percent high school graduate or higher, per capita market income, and transfer payments. Transfer payments per capita are the amount of government benefits a county receives, divided by the county's population, while market income per capita is calculated as total personal income less transfer payments. It can be thought of as the

[7] 18 counties were excluded from the 2016 Form 477 data due to absence or unreliability of broadband data.

income a person earns from participating in the economy, such as what one earns from wages, rental property income, capital gains, pensions, and the like.

Notably, data which are obtained from the American Community Survey (ACS) are reported as either three- or five-year estimates and are calculated as an average across the entire period rather than as an estimate as a point in time. For example, the poverty rate for 2016 is obtained from the 2014-2018 ACS 5-Year estimates. The disadvantage to multiyear estimates is that they are less accurate at pinpointing a snapshot of a statistic at a specific point in time; however, they are often the best available data (and often the only estimates available for geographic areas of less than 65,000 people) and are considered reliable because of large sample sizes, which is particularly relevant for very small areas.

Although this research is primarily concerned with the Appalachian region in general, there is also a focus on rural areas within Appalachia. Because of this dual focus, identifying rural counties is a key component of the data collection. Although there is no standardized definition of what is considered "rural", this paper utilizes two different methods for identifying rural counties: the nine-point USDA Rural-Urban Continuum Codes (RUCC), and the six-point National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme. Each of these classification schemes was last updated in 2013. Of the 420 counties in this dataset, 268, or 63.8%, are classified as rural (RUCC codes 4-9; NCHS codes 5-6). The remaining 152, or 36.2%, are classified as urban (RUCC codes 1-3; NCHS codes 1-4). A more detailed explanation of these codes can be found in Appendix 2.

The USDA-ERS also classifies counties into one of five categories of economic specialization or "dependence" based on the most common type of economic activity in that county: farming, mining, manufacturing, federal/state government, or recreation. A county may also be classified as Nonspecialized, for a total of six possible outcomes for this variable. The classification values for each county reflect 2015 data from the ERS, the most recent data available. This variable provides information about whether one type of economic activity dominates a particular county, and if so, what that economic activity is.

A map of counties identified as Appalachian is provided in Appendix I. Summary statistics tables on all economic variables are provided in Appendix II.

Methods

Following Shideler et al. (2007), this chapter uses a modeling regression technique to estimate the effect of broadband adoption on two key measures of socioeconomic health. The indicators of interest are income (measured as per capita market income) and percentage of individuals who live below the poverty line. These two outcome measures are intuitively related, as poverty status is measured by income, thus, a high percentage of individuals below the poverty line is likely to coincide with a low per capita income (indeed, the correlation coefficient between these two measures is 0.67). However, these outcomes are not interchangeable. While market income provides a snapshot of a representative citizen, percentage below the poverty line gives a wider picture of an area's population as a whole.

Variable definitions and base levels (where appropriate) are provided in Table 2.3. All economic metrics are reported at the county level.

Table 2.3 Explanatory Variables for Model (1), Multivariate Regression Model

Variable Name	Variable Description	Base Category
State	State[8]	Alabama
Dependency	ERS County Typology Code	0 (Nonspecialized)
HSGrad	Percent of adults 25 and older with a high school diploma	Continuous Variable
UER	Unemployment rate (%)	Continuous Variable
RUCC-9	Rural-Urban Continuum Code classification	1 (most urban)
CDCRural	NCHS Urban-Rural Classification Scheme	1 (most urban)
BroadbandScore	Broadband score in the current year	5

This paper uses the FCC's broadband score in a specific year. The model for income and poverty in each year is as follows:

$$Y_{ijklmn} = \mu + BroadbandScore_l + HSGrad_j + UER_k + RUCC\text{-}9_l + Dependency_m + State_n + \varepsilon_{\text{ijklmn}} \qquad (1)$$

Where Y_{ijklmn} is per capita market income (or percentage of people in poverty) for counties with broadband score *i* (on the five-category FCC classification scale), high school graduation percentage level *j*, unemployment rate *k*, county classification *l* (on the nine-point USDA-ERS rural-urban continuum scale), USDA-ERS county economic dependency classification *m* (on the six-category USDA scale), and in state *n*; μ is the overall mean value of per capita market income (or percentage of people in poverty) across all counties under study; $BroadbandScore_i$ is the effect of county broadband classification score *i*, $HSGrad_j$ is the effect of the percentage of individuals age 25 and over with a high school diploma; UER_k is the effect of unemployment rate *k*; $RUCC\text{-}9_l$ is the effect of county classification *l*; $Dependency_m$ is the effect of USDA-ERS county economic dependency classification *m*; $State_n$ is the effect of state *n* (in which the county is located); and ε_{ijklmn} is residual for per capita market income (or percentage of people in poverty)

[8]The 13 states in this analysis are AL, GA, KY, MD, MS, NY, NC, OH, PA, SC, TN, VA, and WV

for counties with broadband score *i*, high school graduation percentage level *j*, unemployment rate *k*, county classification *l* (on the nine-point USDA-ERS rural-urban continuum scale), USDA-ERS county economic dependency classification *m*, and in state *n.*

The model, with income and poverty as the outcomes of interest, was estimated for 2008 and again, separately, for 2016. The size and magnitude of the effects were then compared between the two years to draw conclusions about their relative influence over time.

Since the models for two outcomes (market income and percent in poverty) included the same sets of explanatory variables, multivariate regression methods were used to estimate the two models. This approach results in more robust standard errors as opposed to a stacked ordinary least squares methodology for two individual models. This is particularly useful in situations where the two outcome variables are thought to be highly correlated, or where there may be latent causes influencing both outcomes. This is likely to be the case in this dataset, as income, poverty, unemployment, and education often covary with each other. For this reason, a multivariate regression technique was considered to be most appropriate, so as to yield more precise standard errors.

2.3 RESULTS

The results of the multivariate regressions measuring the relationships between county-level household broadband connections high school graduation rate, unemployment rate, rural classification, and ERS County Typology code and the outcome variables of interest: per capita market income (i.e., the income that people earn from participating in the economy through wages, rental property income, investments, and the like: all non-governmental income), and percent of people living below the poverty line are reported in Tables 2.4 – 2.7.

Broadband adoption level “5” – greater than 800 connections per thousand residents, or 80%+ adoption – was used as the base category for these models. In 2008, there were ten counties with less than 20% adoption; in 2016, there were none. Thus, the highest category was selected as the base group.

In 2008, a statistically significant association between broadband and market income was only observed for the lowest levels of broadband adoption. Counties in the “1” category had per capita market incomes $2,405 lower on average than counties in the “5” category, a result which was significant at the 5% level. Similarly, counties in the “2” group (201-400 connections per thousand) had market incomes $1,751 lower on average than the most connected counties, which was only marginally significant at the 10% level (p-value 0.099). Counties in the “3” and “4” categories did not have a significantly different per capita market income than the most-connected counties. However, in 2016, lower broadband adoption was significantly associated with lower market income for all categories, and two of the three were significant at the 1% level. Counties in the “2” category had per capita incomes $2,833 less on average than category “5” counties, which was significant at the 5% level. Counties in the “3” and “4” categories had per capita market incomes which were on average $4,000 and $2,577 less, respectively, than counties in the “5” group.

Broadband was not significantly associated with poverty in 2008. In 2016, only categories in the “2” group were associated with higher poverty rates on average than counties with the highest levels of broadband adoption. The coefficient was large – 3.78 percentage points – and the result was significant at the 1% level. This suggests that the relative importance of broadband has increased over time, and as more counties shift into the higher adoption rate categories, those counties that continue to have low adoption levels may be getting left behind.

High school graduation rate and unemployment had the expected signs for both outcomes of interest and were significant at the 1% level for both outcomes in both years. Interestingly, for percentage of people in poverty, the coefficient for unemployment rate nearly doubled from 2008 to 2016: in 2008, a one percentage point increase in the unemployment rate led to a 0.524 percentage point increase in the percentage of people in poverty. In 2016, a one percentage point increase in unemployment rate led to a 1.043 percentage point increase in the percent of people in poverty.

On the nine-point RUCC scale, in 2008, market income per capita was lower by $1,220-$3,172 on average for all categories relative to the base category (most urban) of "1". Differences were significant at the 1% level for all categories other than level 2 (significant at the 5% level) and level 5 (not significant). In 2016, however, differences were not significant for counties in levels 2, 3, or 5. Counties in levels 1-3 are considered metropolitan, while counties in levels 4-9 are considered nonmetro. A possible explanation for these results is that smaller cities, or cities in smaller metropolitan areas, are becoming more competitive with cities in larger metropolitan areas.

Notably, among all other counties (levels 4 and 6-9), per capita market income was lower by $2,822-$5,488 on average relative to the most urban counties, and these results were significant at the 1% level. Among the most rural counties, RUCC-9, per capita market income was $5,488 lower on average than the most urban, RUCC-1 counties. This difference was over $2,000 lower than the next-largest difference ($3,269 less than the most urban counties in RUCC-6).

Similarly, poverty was between 1.81 and 5.12 percentage points higher in 2008 relative to the base category for categories 3-9, all of which were significant at the 1% level except for category 8 (significant at the 5% level). Category 8 was not significant at all in 2016; among other categories in the 3-9 range, all were between 1.76 and 4.48 percentage points higher than the base category of 1 and all were significant at the 1% level except for category 7 (significant at the 5% level). It should be noted that there was no consistent pattern of progression observed as the counties became more and more rural (i.e., the coefficients did not continually increase). When comparing metro-adjacent and non-metro-adjacent counties of similar size, poverty was higher in non-adjacent counties in categories 5 and 9 relative to categories 4 and 8 (urban populations of 20,000 or more and 2,500 or less, respectively). The most striking difference was between counties in levels 8 and 9 in 2016. There was no difference between poverty in RUCC-8 counties and the most urban counties, while poverty was 3.15 percentage points higher on average than the base category in RUCC-9 counties, significant at the 1% level. These are all rural counties with urban populations of 2,500 or less; the differentiating factor is that RUCC-8 is adjacent to a metro area while RUCC-9 is not. Taken together with the results for market income, this result further suggests that the most remote, rural counties may be getting left behind.

Poverty was higher (1.43 percentage points) and income was lower (-$1,108) in 2008 in counties where the primary economic activity was governmental as opposed to nonspecialized; this result was similar but more pronounced in 2016: poverty was 1.98 percentage points higher on average, per capita market income was $1,919 lower on average. Poverty was lower in both years for manufacturing-dependent counties – 1.52 percentage points in 2008 and 1.40 percentage points in 2016 – but there was no difference in per capita market income in either year. In 2016, mining-dependent counties had per capita market income $1,384 higher on average relative to nonspecialized counties, but there was no difference in poverty in either year. Per capita market income was lower on average in farming-dependent counties in both years ($1,821 in 2008 and $2,823 in 2016), but there was no difference in poverty.

Table 2.4*: Multivariate Model Results: Market Income Per Capita (in 000s), 2008*

	Coefficient	SE	p-value
Constant	8.406	2.927	0.004***
Broadband Category			
1	-2.405	1.199	0.046**
2	-1.751	1.058	0.099*
3	-0.645	1.010	0.523
4	1.447	1.037	0.164
5	*base*		
% High School Graduates	0.302	0.030	0.000***
Unemployment Rate	-0.948	0.114	0.000***
Rural-Urban Continuum Code			
1	*base*		
2	-1.220	0.563	0.031**
3	-2.042	0.578	0.000***
4	-2.167	0.608	0.000***
5	-1.220	1.031	0.238
6	-2.714	0.547	0.000***
7	-2.150	0.615	0.001***
8	-2.141	0.649	0.001***
9	-3.172	0.676	0.000***
Dependency			
Nonspecialized	*base*		
Farming	-1.821	0.777	0.020**
Mining	-0.766	0.522	0.143
Manufacturing	0.110	0.324	0.735
Federal/State Govt.	-1.108	0.429	0.010***
Recreation	-0.944	0.483	0.051*
State			
Alabama	*base*		
Georgia	-0.341	0.607	0.574
Kentucky	-2.508	0.617	0.000***
Maryland	0.837	1.524	0.583
Mississippi	-0.734	0.742	0.323
New York	-2.893	0.878	0.001***
North Carolina	-0.536	0.674	0.427
Ohio	-2.661	0.665	0.000***
Pennsylvania	-2.542	0.614	0.000***
South Carolina	0.425	1.143	0.710
Tennessee	-0.525	0.565	0.354
Virginia	-1.081	0.679	0.112
West Virginia	-3.377	0.581	0.000***
R^2	77.25%		
# Obs.	420		

**** = Significant at 1% level*
*** = Significant at 5% level*
** = Significant at 10% level*

Table 2.5*: Multivariate Model Results: Percent in Poverty, 2008*	Coefficient	SE	p-value
Constant	41.033	4.018	0.000***
Broadband Category			
1	*0.682*	1.645	0.679
2	-0.797	1.452	0.584
3	-1.181	1.387	0.395
4	-0.619	1.423	0.664
5	*base*		
% High School Graduates	-0.362	0.041	0.000***
Unemployment Rate	0.524	0.157	0.001***
Rural-Urban Continuum Code			
1	*base*		
2	0.883	0.773	0.254
3	3.129	0.794	0.000***
4	3.023	0.835	0.000***
5	5.124	1.415	0.000***
6	2.235	0.751	0.003***
7	2.687	0.844	0.002***
8	1.811	0.891	0.043**
9	2.616	0.928	0.005***
Dependency			
Nonspecialized	*base*		
Farming	-0.178	1.066	0.868
Mining	1.148	0.716	0.110
Manufacturing	-1.524	0.445	0.001***
Federal/State Govt.	1.425	0.588	0.016**
Recreation	-1.047	0.664	0.115
State			
Alabama	*base*		
Georgia	-0.511	0.832	0.539
Kentucky	4.102	0.847	0.000***
Maryland	-2.531	2.092	0.227
Mississippi	3.320	1.018	0.001***
New York	0.821	1.204	0.496
North Carolina	1.173	0.924	0.205
Ohio	1.410	0.912	0.123
Pennsylvania	-0.821	0.843	0.331
South Carolina	0.889	1.569	0.571
Tennessee	0.867	0.776	0.264
Virginia	-1.725	0.932	0.065*
West Virginia	1.853	0.797	0.021**
R^2	68.29%		
# Obs.	420		

**** = Significant at 1% level*
*** = Significant at 5% level*
** = Significant at 10% level*

Table 2.6*: Multivariate Model Results: Market Income Per Capita (in 000s), 2016*	Coefficient	SE	p-value
Constant	9.551	4.168	0.022**
Broadband Category			
2	-2.833	1.288	0.028**
3	-4.000	0.708	0.000***
4	-2.577	0.557	0.000***
5	*base*		
% High School Graduates	0.339	0.044	0.000***
Unemployment Rate	-1.168	0.141	0.000***
Rural-Urban Continuum Code			
1	*base*		
2	-1.055	0.757	0.164
3	-1.259	0.772	0.104
4	-2.822	0.796	0.000***
5	-0.841	1.347	0.533
6	-3.269	0.725	0.000***
7	-2.972	0.814	0.000***
8	-3.206	0.866	0.000***
9	-5.488	0.914	0.000***
Dependency			
Nonspecialized	*base*		
Farming	-2.823	1.044	0.007***
Mining	1.384	0.759	0.069
Manufacturing	-0.137	0.434	0.753
Federal/State Govt.	-1.919	0.582	0.001***
Recreation	-1.298	0.667	0.053*
State			
Alabama	*base*		
Georgia	-1.719	0.822	0.037**
Kentucky	-1.649	0.827	0.047**
Maryland	1.926	1.973	0.329
Mississippi	-1.305	0.949	0.170
New York	-0.594	1.100	0.590
North Carolina	-2.451	0.892	0.006***
Ohio	-0.258	0.823	0.754
Pennsylvania	1.729	0.794	0.030**
South Carolina	0.312	1.472	0.832
Tennessee	-1.933	0.722	0.008***
Virginia	-0.292	0.876	0.739
West Virginia	-2.257	0.769	0.004***
R^2	72.21%		
# Obs.	402		

**** = Significant at 1% level*
*** = Significant at 5% level*
** = Significant at 10% level*

Table 2.7*: Multivariate Model Results: Percent in Poverty, 2016*

	Coefficient	SE	p-value
Constant	33.763	3.995	0.000***
Broadband Category			
2	3.776	1.234	0.002***
3	0.904	0.678	0.183
4	0.805	0.534	0.132
5	*base*		
% High School Graduates	-0.297	0.042	0.000***
Unemployment Rate	1.043	0.135	0.000***
Rural-Urban Continuum Code			
1	*base*		
2	0.698	0.725	0.336
3	1.974	0.740	0.008***
4	2.257	0.763	0.003***
5	4.476	1.291	0.001***
6	2.004	0.695	0.004***
7	1.756	0.780	0.025**
8	0.669	0.830	0.421
9	3.154	0.876	0.000***
Dependency			
Nonspecialized	*base*		
Farming	0.047	1.000	0.962
Mining	0.240	0.728	0.741
Manufacturing	-1.402	0.416	0.001***
Federal/State Govt.	1.980	0.558	0.000***
Recreation	-1.116	0.640	0.082*
State			
Alabama	*base*		
Georgia	-0.789	0.788	0.317
Kentucky	3.641	0.792	0.000***
Maryland	-2.849	1.890	0.133
Mississippi	2.179	0.910	0.017**
New York	1.053	1.054	0.318
North Carolina	0.919	0.855	0.283
Ohio	0.168	0.789	0.832
Pennsylvania	-2.474	0.761	0.001***
South Carolina	1.244	1.411	0.378
Tennessee	1.421	0.691	0.041**
Virginia	-0.229	0.839	0.785
West Virginia	-0.244	0.737	0.741
R^2	70.61%		
# Obs,	402		

**** = Significant at 1% level*
*** = Significant at 5% level*
** = Significant at 10% level*

3. CHAPTER III: FACTORS INFLUENCING EXCESS MORTALITY IN APPALACHIA: DOES RURALITY MATTER?

3.1 Introduction and Background

In 2017, the Centers for Disease Control (CDC) issued a report examining the number of potential excess deaths in rural areas as opposed to urban areas. Excess deaths were defined as deaths from the five leading causes of mortality for persons under the age of 80 (CDC 2017). This report was expanded upon in late 2019 by further disaggregating the geographical units of analysis into six levels of rural/urban granularity as opposed to two (rural and urban). In both reports, the CDC analysis found that, nationally, "[n]onmetropolitan counties had higher percentages of potentially excess deaths from the five leading causes than metropolitan counties during 2010–2017 nationwide, across public health regions, and in the majority of states" (CDC 2019). This analysis did not, however, take other county characteristics into account. This chapter is an effort to cover the aforementioned gap in knowledge

Individuals living in rural areas experience consistently inferior health outcomes compared to individuals in urban and suburban areas, and some research suggests that the disparity is becoming more pronounced over time (Cosby et al. 2019, Laditka et al. 2009). Americans in rural communities are more likely to die from diabetes-related hospitalizations (Ferdinand et al. 2019) and atrial fibrilation hospitalizations (O'Neal et al. 2018) than their nonrural counterparts. They self-report unmet dental needs, including fewer recent dental visits, at a higher level than Americans in nonrural areas, and are almost twice as likely to report edentulism (toothlessness) (Vargas et al. 2002). From a regional perspective, residents in Appalachia, particularly rural Appalchia, generally experience inferior health outcomes relative to other regions in the United States. An extensive 2017 report by the Appalchian Regional

Commission detailed that the region underperformed the national average on 33 of 41 health indicators, including seven of the ten leading causes of death in the United States (ARC). These indicators included a diverse array of health dimensions, including self-reported mentally and physically unhealthy days, health behaviors such as obesity and tobacco use, infant mortality and teen pregnancy, and supply of physicians. The region also had substantially higher mortality rates than the national average for heart disease, stroke, diabetes, cancer, COPD, and injury (ARC). Of note, the report also found differences between urban and rural communities within the region.

Urban-rural health disparities may be due to several factors. Issues specific to rural areas, such as a long distance to care providers due to geographic dispersion, may hinder the population from receiving care. Alternatively, to the extent that poverty and low income status are more ubiquitous in rural areas than urban or suburban areas, solutions may be more effective if they focus on the general socioeconomic health of rural communities. Indeed, Long et al. (2018) found that when socioeconomic variables were controlled for, the inclusion of a rural-urban variable improved model fit by only two percentage points. They conclude that efforts to ameliorate socioeconomic issues are likely to be more effective at improving rural health outcomes, rather than those focused strictly on healthcare reform.

One way to mitigate these issues may be through the use of telehealth and telemedicine. Although the use of telemedicine and virtual treatment increased considerably in 2020 due to the COVID-19 pandemic, gaps remain in the availability and use of telehealth, including in provider training and education (Rutledge et al. 2017). At present, significant impediments to widespread implementation include regulatory hurdles including licensure requirements, lack of financial support for telehealth programs, lack of adequate bandwidth in rural areas, and lack of technological skill among patients (Gajarawala et al. 2020, Kedia et al. 2021). However, there are many benefits of telehealth and telemedicine, particularly in geographically dispersed populations. Raza et al. (2009) found that telemedicine saved pulmonary patients at the Milwaukee Veteran Affairs Medical Center 294,120 miles of travel during the years of 1998-2004. Bian et al. (2019) found that a school-based telehealth program in rural South Carolina was associated with a 21% decline in emergency visits due to asthma for children ages 3-17 who were enrolled in Medicaid, although there was no difference in the overall number of emergency visits. Current research suggests that telehealth may provide the most benefit when it is used to supplement, but not replace, in person interaction, and usefulness may vary by treatment speciality and type of care delivered (Gajarawala et al. 2020, Wang et al. 2020). For example, one study of telehealth substance abuse treatment in Appalachian Tennessee suggested that patients may benefit more from face-to-face interaction, but telemedicine consultations may be useful for writing prescriptions for methadone (Kedia et al. 2021).

This section of the thesis uses an ordinary least squares (OLS) regression to assess the impact of an array of socioeconomic variables on excess mortality, with the objective of isolating the impact of rurality on excess deaths. In the context of the previous section, the impact of broadband on excess mortality is also of interest.

3.2 Data

Data on excess mortality for the five leading causes of death were obtained from the Center for Disease Control and Prevention (CDC) WONDER database[9]. Per the CDC, these causes of death are heart disease, cancer, unintentional injury, chronic lower respiratory disease (CLRD), and stroke (CDC 2017). These data were extracted, on a county level, for the years 2008 and 2016 for all individuals under the age of 80 who died from any of these causes. The data are reported on a per-100,000-resident basis; i.e., if the excess mortality figure for a given county in a

[9] Accessed November 12, 2020

given year is 200, that is to be interpreted as 200 excess deaths per 100,000 residents. Throughout this section of the paper, "excess mortality" will refer to the rate of potential excess deaths in a given county in a given year. This number is the outcome of interest for this model.

To enable consistency with the CDC research, rural classification was assigned based on a six-point urban-rural county scale developed by the National Center for Health Statistics (NCHS) instead of the nine-point Rural-Urban Continuum Codes (RUCC) produced by the USDA-ERS, which is used in the previous section of the paper. The NCHS scale is the scale used in the CDC's research, and separates counties into six classifications: large central metro, large fringe metro, medium metro, small metro, micropolitan, and non-core (CDC 2014). Like the RUCC, the NCHS scale was last updated in 2013.

All other socioeconomic data and broadband subscription data are the same as those used in the previous section; that is, socioeconomic data are obtained from the Appalachian Regional Commission (ARC) and broadband data are obtained from the FCC's Form 477.

Variable definitions and base levels (where appropriate) are provided in Table 3.1. All economic metrics are reported at the county level.

Table 3.1 Explanatory Variables for Model (2), OLS Regression Model

Variable Name	Variable Description	Base Category
Year	Year of Observation (2008 or 2016)	2008
State	State	Alabama
Dependency	ERS County Typology Code	0 (Nonspecialized)
HSGrad	Percent of adults 25 and older with a high school diploma	Continuous Variable
MarketIncome	Income less transfer payments ($000s)	Continuous Variable
Poverty	Share of the population below the Federal poverty line (%)	Continuous Variable
UER	Unemployment rate (%)	Continuous Variable
CDCRural	NCHS Urban-Rural Classification Scheme	1 (most urban)
BroadbandScore	Broadband score in the current year	5

3.3 Methods

To estimate the effects of these explanatory variables on excess mortality, I use an ordinary least squares (OLS) regression. The dependent variable is the rate of excess deaths on a per-100,000-resident basis in a given county for the year 2016. The set of explanatory variables is the same set as is used in the previous section, as well as transfer payments, market income, and percentage in poverty; a full list of explanatory variables and variable definitions can be found in Table 3.1 above. The observational group includes all counties identified as "Appalachian" by the ARC.

The model for excess mortality rate is as follows:

$$Y_{ijklmnopq} = \mu + BroadbandScore_l + HSGrad_j + UER_k + CDCRural_l + Dependency_m + State_n$$
$$+ MarketIncome_o + Poverty_p + Transfer_q + \varepsilon_{ijklmnopq} \quad (2)$$

Where $Y_{ijklmnopq}$ is excess deaths per 100,000 residents for counties with broadband score i (on the five-category FCC classification scale), high school graduation percentage level j, unemployment rate k, county classification l (on the five-point CDC-NCHS rural-urban continuum scale), USDA-ERS county economic dependency classification m (on the six-category USDA scale), in state n, with per capital market income o, percentage of people in poverty p, and transfer payments per capita q; μ is the overall mean value of excess deaths per 100,000 residents across all counties under study; $BroadbandScore_i$ is the effect of county broadband classification score i, $HSGrad_j$ is the effect of the percentage of individuals age 25 and over with a high school diploma; UER_k is the effect of unemployment rate k; $RUCC\text{-}9_l$ is the effect of county classification l; $Dependency_m$ is the effect of USDA-ERS county economic dependency classification m; $State_n$ is the effect of state n (in which the county is located), $MarketIncome_o$ is the effect of market income per capita (in thousands), $Poverty_p$ is the effect of the percentage of people below the federal poverty line, and $Transfer_q$ is the effect of transfer payments – i.e., benefits or subsidies paid by the government – in thousands; and $\varepsilon_{ijklmnop}$ is residual for excess deaths per 100,000 residents for counties with broadband score *i* (on the five-category FCC classification scale), high school graduation percentage level *j*, unemployment rate *k*, county classification *l* (on the nine-point USDA-ERS rural-urban continuum scale), USDA-ERS county economic dependency classification *m* (on the six-category USDA scale), in state *n*, with per capital market income *o*, percentage of people in poverty *p*, and transfer payments per capita *q*.

3.4 Results

As mentioned in the methods section, to enable consistency with the CDC's paper on excess mortality in rural areas, this regression was run using the NCHS six-point urban-rural county scale. Notably, there were no major differences between these results and those run with the RUCC nine-point scale[10].

The largest and most significant of the explanatory variables was transfer payments per capita. A $1,000 increase in transfer payments was associated with 38.02 more deaths per 100,000 residents on average, and was significant at the 1% level. This is not a surprising result if one considers that, when assistance programs function properly, funds are allocated to the communities in greatest need. Thus a county with poor health outcomes is likely to receive more funding from assistance programs. Surprisingly, however, there was no statistically significant relationship between percent in poverty and excess mortality, nor was there a relationship between unemployment rate and excess mortality.

There were modest associations between excess mortality and high school graduation rate and market income per capita. A one percentage point increase in high school graduation rate was associated with 2.74 fewer excess deaths per 100,000 residents on average, while a $1,000

[10]For the sake of brevity, the results of the model using the nine-point RUCC scale are not depicted.

increase in per capita market income was associated with 4.30 fewer deaths. Both were significant at the 1% level. There was no relationship between broadband and excess mortality.

With respect to county economic activity, the most notable result was a higher excess mortality rate in mining-dependent counties, which had 36.41 more excess deaths per 100,000 residents on average than nonspecialized counties, and manufacturing counties, which had 22.96 more excess deaths on average than nonspecialized counties. Both were was significant at the 5% level. As noted in the data section, excess mortality refers to deaths of individuals under 80 from the five leading causes of death, which includes chronic lower respiratory diseases and unintentional injury. This finding of higher excess mortality in mining and manufacturing counties is unsurprising, given the highly physical nature of both types of work and the possibility of accidents, as well as the incidence of respiratory issues miners often face.

Most notably, this paper found no statistically significant association between county rural classification using the six-digit CDC scale and excess mortality when other factors were included in the regression, contrary to earlier findings by the CDC. When using the nine-point RUCC scale, this analysis found modestly lower levels of excess mortality – 30-40 deaths per 100,000 residents on average – in RUCC-3 (metro areas of fewer than 250,000) and RUCC-4 (urban population of 20,000 or more, metro-adjacent) counties, significant at the 5% level, and RUCC-7 (urban population of 2,500-19,999, nonadjacent) counties, significant the 10% level.

There are several possible explanations for this result. One is that the dataset used in this analysis focuses on a specific and fairly homogeneous geographic area. Only two counties are classified as large metro[11] (NCHS-1); another 35 are large fringe metro (NCHS-2). It may be that rural and urban areas of Appalachia are less dissimilar than urban and rural areas in general, or in

[11]The two counties and their respective cities are Allegheny County, PA (Pittsburgh), and Jefferson County, AL (Birmingham)

regions that are drawn more primarily by geographic lines than by a combination of geographic and cultural lines.

Alternatively, and perhaps the more robust explanation, is that the CDC analysis strictly examined mortality by rural status and did not take other factors into account (e.g. income, poverty, etc.). The current analysis suggests that these additional factors may be contributing to the urban/rural health gap, rather than the differences being purely or primarily due to issues unique to rural communities. Table 3.2 shows the full results of the OLS regression.

Table 3.2*: Excess Mortality Per 100,000 Population, 2016*			
	Coefficient	SE	p-value
Constant	540.844	109.330	0.000***
Broadband Category			
2	-37.514	23.638	0.176
3	23.484	14.815	0.114
4	1.561	11.471	0.892
5	*base*		
% High School Graduates	-2.738	0.995	0.006***
Unemployment Rate	0.217	3.431	0.950
Market Income Per Capita (000s)	-4.296	1.096	0.000***
Percent of People in Poverty	-0.920	1.118	0.411
Transfer Payments Per Capita (000s)	38.020	2.886	0.000***
NCHS (CDC) Rural-Urban Code			
1	*base*		
2	-5.213	49.443	0.916
3	-12.212	48.972	0.803
4	-37.851	49.025	0.441
5	-29.174	49.267	0.554
6	-27.398	49.505	0.580
Dependency			
Nonspecialized	*base*		
Farming	19.085	20.979	0.364
Mining	36.410	15.471	0.019**
Manufacturing	22.961	9.026	0.011**
Federal/State Govt.	-8.059	12.779	0.529
Recreation	0.424	13.577	0.975
State			
Alabama	*base*		
Georgia	-44.660	17.001	0.009***
Kentucky	-59.400	17.308	0.001***
Maryland	-121.158	40.310	0.003***
Mississippi	-69.396	18.528	0.000***
New York	-116.626	22.217	0.000***
North Carolina	-95.161	18.134	0.000***
Ohio	-69.902	16.684	0.000***
Pennsylvania	-103.527	16.553	0.000***
South Carolina	-87.430	29.735	0.003***
Tennessee	-18.483	14.881	0.215
Virginia	-79.047	17.912	0.000***
West Virginia	-83.175	15.730	0.000***
R^2	71.69%		
# Obs.	398		

***** = *Significant at 1% level***
**** = *Significant at 5% level***
*** = *Significant at 10% level***

4. CHAPTER IV: DISCUSSION AND CONCLUSIONS

This thesis sought to evaluate the impact of increases in broadband adoption and several other socioeconomic variables on income and percentage of people in poverty in the Appalachian region of the United States, as well as the impact of socioeconomic variables on excess mortality within an established context of a rural-urban health gap. Consistent with previous studies, including Whitacre et al. (2014), this thesis found a positive and statistically significant relationship between broadband adoption and income specifically in counties where adoption rates exceeded 60%. This thesis also found a negative, and modest, relationship between broadband and both poverty rate and excess mortality, likewise in counties where broadband adoption is greater than 60%. Notably, this thesis did not find a progressive relationship between subscribership and socioeconomic factors at intermediate levels of broadband adoption. This suggests that the benefits of broadband adoption in a community are not fully realized until broadband adoption is widespread.

In order to properly interpret these results, it is worth addressing what is meant by "access to broadband". In order to conduct a comparison of coverage and subscription over time, it was necessary to use the FCC's original threshold of 200kbps in any direction for an area to be considered "served". A testament to how quickly technology changes, this threshold was obsolete just a few years later: the FCC's 2016 Broadband Progress Report used 25mbps upstream/3mbps downstream as its speed threshold for considering an area served. In the context of these results, it is possible that access and subscription to broadband at lower speeds did not have as strong of an impact as might have been expected. It may be difficult for users to realize the benefits of Internet access when service is slow, spotty, and unreliable (Mack 2018). Furthermore, Form 477 data depicting high levels of subscribership are, to some extent, misrepresenting the true conditions of broadband access in that area if low-speed service is little better than no service at all.

Alternatively, it may be that broadband is a luxury good: in wealthier communities, more people are likely to have an Internet connection at home. Establishing the direction of causality between broadband adoption and economic health variables is not necessarily straightforward. Insofar as Internet access in the home is a consumable good, it may be considered a luxury to be enjoyed once an individual or household achieves a given level of prosperity, rather than primarily as a tool for achieving that prosperity in the first place. Further, for a community experiencing high unemployment, low income, and high poverty, it should be unsurprising that a small percentage of households chooses to subscribe to Internet access at home, as necessities like food and shelter take priority. High residential subscription rates may, then, be a result of prosperity rather than a cause. Further research might shed light on the direction of causality between broadband and socioeconomic health.

From a research and policymaking perspective, ascertaining the direction of causality should be a primary focus in determining how broadband investment dollars should be appropriated. Often the most expensive piece of broadband deployment is providing the "last mile", particularly in rural areas with geographically dispersed populations. If those households cannot afford a monthly Internet subscription, the usefulness of providing the last mile is limited. If this is the case, the most efficient use of broadband grants might be providing public access to broadband via schools, libraries, or community connection centers. If broadband availability is a contributing factor to increased incomes and decreased poverty, then the continuation of broadband grants is supported.

Additionally, data quality and accuracy – or lack thereof – currently represents a significant roadblock both in mapping broadband availability and understanding its impact. To date, FCC data is often collected on the provider side. Collecting and reporting data on the consumer side, such as through a broadband census, and reporting at the location level could improve the accuracy and precision of the data available to researchers and policymakers. Georgia, in fact, has undertaken such an initiative in the past two years. Recognizing the unreliability of FCC data, the Georgia Broadband Deployment Initiative began mapping broadband at the location level. The GBDI maps found that far fewer households had access to broadband than the FCC data reported (Georgia Broadband Deployment Initiative). Because poor data inhibits efficacy and accuracy of analysis, it is of paramount importance to have a foundation of accurate data for conducting analysis and forming legislative policy. Enhancing data quality should therefore be a fundamental piece of broadband legislation going forward.

Further research could also address the role of broadband, whether through household connections or community access points, in promoting physical health, particularly in rural areas. Strong broadband service can enable patients to receive care remotely as well as promote health education, which would help to ameliorate some of the behavioral health problems, such as obesity and tobacco use, that are particularly severe in Appalachia. Consistent with Long et al. (2018), this thesis found that the primary driver of rural-urban differences in excess mortality was socioeconomic factors, rather than the condition of being rural. Efforts aimed at bettering the overall quality of life for Americans in rural communities, particularly in historically underserved areas like Appalachia, can help lead to better physical health outcomes as well.

From a research perspective, conducting research at highly granular geographic levels, while potentially offering valuable information, also presents unique challenges. Census tract redistricting every ten years makes drawing conclusions over time challenging, particularly when population growth requires census tracts to be split. Small changes in a community's population can cause seemingly dramatic shifts in measurements of the population's characteristics, particularly for areas with very small populations. That said, county-level analysis frequently falls short due to intra-county differences in population characteristics, particularly in geographically large counties that have a larger city and many rural areas far from the city center. A possible solution to these issues might be making Census data more easily connectable to ZIP codes, which can be more user-friendly for policymakers on the local and state level.

On a larger scale, along those lines, more uniformity and consensus regarding definitions of “rural” and “urban” might be a useful development in advancing research and policy affecting Americans in rural communities. Throughout this research, many places were identified whose classifications did not seem to reflect the true character of the area[12], which begs the question of “What is rural?”. Although different agencies might utilize different classifications based on their individual objectives, it may be useful to achieve some degree of uniformity and cohesion to the extent that each of these agencies has the common goal of promoting health, education, and other social services for Americans in rural communities.

[12] For example, using rural-urban continuum codes (RUCC) and rural-urban commuting area (RUCA) codes and the HRSA’s modification, Chester County, South Carolina is identified as an “urban” county; five of its 11 Census tracts are RUCA code 2 and the remaining six are RUCA code 3. The county itself is RUCC-1, the most urban designation possible. At the same time, according to the US Census Bureau just 28% of Chester County’s population and only 1.2% of its land area are classified as urban. The most straightforward explanation for this phenomenon is that Chester County is located within the Charlotte metropolitan area and thus sees a high commuting flow to an urbanized area.

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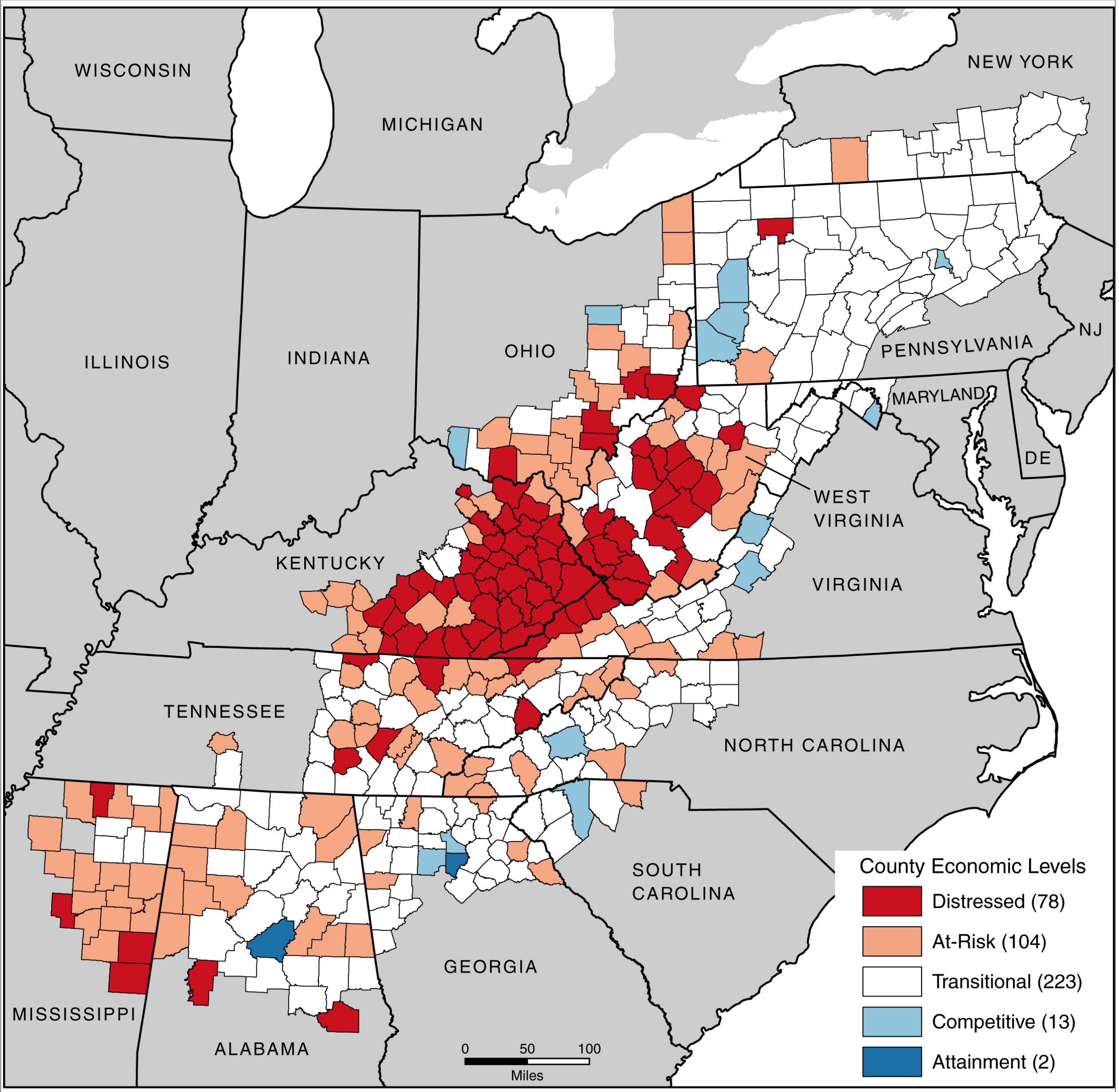
6. APPENDIX I:

Counties Identified As Appalachian by Fiscal Year 2021 Economic Status



Created by the Appalachian Regional Commission, June 2020
Data Sources:
Unemployment data: U.S. Bureau of Labor Statistics, LAUS, 2016–2018
Income data: U.S. Bureau of Economic Analysis, REIS, 2018
Poverty data: U.S. Census Bureau, American Community Survey, 2014–2018

Effective October 1, 2020
through September 30, 2021

7. APPENDIX II: VARIABLES AND DATA SOURCES

Variable Name	Variable Description	Data Source
Year	Year of Observation (2008 or 2016)	
State	State	n/a
Dependency	ERS County Typology Code	USDA Economic Research Service
HSGrad	Percent of adults 25 and older with a high school diploma	Appalachian Regional Commission (ARC)
MarketIncome	Income less transfer payments ($000s)	ARC
Poverty	Share of the population below the Federal poverty line (%)	ARC
UER	Unemployment rate (%)	ARC
CDCRural	NCHS Urban-Rural Classification Scheme	National Center for Health Statistics
BroadbandScore	Broadband score in the current year	Federal Communications Commission, Form 477

8. APPENDIX III: RURAL-URBAN CLASSIFICATIONS

USDA-ERS Rural-Urban Continuum Codes, 2013

Metropolitan Counties

Code	Description
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population

Nonmetropolitan Counties

Code	Description
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area

NCHS (CDC) Rural -Urban Classification Codes, 2013

Metropolitan Counties

Code	Description
1	Large Central Metro
2	Large Fringe Metro
3	Medium Metro
4	Small Metro

Nonmetropolitan Counties

Code	Description
5	Micropolitan
6	Non-Core

9. APPENDIX IV: SUMMARY STATISTICS

Summary Statistics: Excess Mortality

	N	Mean	StDev	Min	25th	Med	75th	Max
Alabama								
2008	37	501.87	102.17	242.40	441.70	517.40	547.60	729.20
2016	37	555.48	113.31	295.10	493.60	569.20	622.80	778.30
Georgia								
2008	37	378.90	102.60	165.20	306.10	390.50	476.60	547.70
2016	37	461.90	130.84	190.70	383.70	457.20	559.00	703.60
Kentucky								
2008	53	554.84	94.88	322.70	492.40	565.50	620.10	815.80
2016	53	642.08	114.49	371.80	564.80	647.40	707.00	901.10
Maryland								
2008	3	381.63	43.10	331.90	331.90	404.90	408.10	408.10
2016	3	425.17	49.95	375.10	375.10	425.40	475.00	475.00
Mississippi								
2008	24	487.95	109.36	237.80	406.15	490.20	567.85	675.00
2016	24	531.73	93.41	274.60	461.85	544.55	582.65	677.10
New York								
2008	14	352.54	62.06	202.00	325.50	354.60	392.80	440.60
2016	14	389.44	65.61	256.00	364.30	382.35	435.90	514.00
North Carolina								
2008	29	439.35	78.54	231.90	403.70	442.50	497.80	576.40
2016	29	462.49	79.85	212.60	429.30	481.40	505.60	577.00
Ohio								
2008	32	442.52	81.28	211.40	410.55	448.50	496.25	623.40
2016	32	492.17	88.94	285.30	442.85	492.25	559.15	660.20
Pennsylvania								
2008	52	405.88	58.88	216.90	375.85	418.85	449.25	511.30
2016	51	433.99	78.99	190.50	390.60	438.80	485.20	665.60
South Carolina								
2008	6	415.70	65.71	333.30	389.60	399.70	443.50	528.40
2016	6	433.40	50.97	348.20	407.10	444.40	471.70	484.60
Tennessee								
2008	51	493.77	81.69	358.30	426.50	479.40	550.10	774.20
2016	52	569.82	109.77	391.10	501.60	554.80	618.80	837.30
Virginia								
2008	24	495.59	103.80	216.00	432.15	502.70	555.30	661.70
2016	24	515.58	114.56	228.50	462.80	544.05	591.65	675.30
West Virginia								
2008	55	488.44	100.97	257.00	423.60	474.20	550.80	778.20
2016	55	516.21	90.52	271.10	464.50	510.20	556.10	810.60

Summary Statistics: High School Graduation (% of People Age 25+)

	N	Mean	StDev	Min	25th	Med	75th	Max
Alabama								
2008	37	76.67	5.56	68.10	73.10	75.50	80.10	91.50
2016	37	82.30	4.02	74.10	80.20	81.80	84.30	92.20
Georgia								
2008	37	77.88	6.12	66.20	73.30	77.90	82.10	90.60
2016	37	82.44	5.43	69.30	79.10	83.00	86.00	92.80
Kentucky								
2008	54	69.57	6.30	56.80	66.20	68.85	73.40	83.90
2016	54	76.50	5.00	64.30	73.40	75.95	79.00	88.50
Maryland								
2008	3	84.27	0.85	83.40	83.40	84.30	85.10	85.10
2016	3	88.73	1.63	86.90	86.90	89.30	90.00	90.00
Mississippi								
2008	24	74.55	4.74	66.00	71.60	74.95	77.70	84.50
2016	24	79.77	4.51	69.90	77.70	79.65	82.35	90.50
New York								
2008	14	87.86	1.72	85.00	87.00	87.55	88.30	92.40
2016	14	90.03	1.55	88.20	88.90	90.00	90.70	94.20
North Carolina								
2008	29	80.17	4.67	71.40	76.80	79.40	84.10	87.20
2016	29	84.54	4.21	76.60	81.00	84.20	88.50	91.00
Ohio								
2008	32	82.38	5.82	56.30	80.55	83.80	86.00	88.00
2016	32	85.45	5.97	57.60	84.35	86.25	88.90	90.90
Pennsylvania								
2008	52	86.57	2.89	80.10	85.30	86.70	88.50	92.60
2016	52	89.65	2.61	82.40	88.35	89.70	91.05	94.60
South Carolina								
2008	6	80.22	3.26	74.20	79.90	80.90	81.40	84.00
2016	6	84.33	2.68	79.60	83.90	84.70	85.30	87.80
Tennessee								
2008	52	75.69	5.48	64.30	71.55	74.95	79.85	88.30
2016	52	82.25	3.99	74.90	79.05	82.35	84.95	91.00
Virginia								
2008	25	76.53	6.21	63.70	73.40	75.70	80.30	89.20
2016	25	83.50	5.88	70.30	79.40	84.70	86.90	92.60
West Virginia								
2008	55	79.76	6.11	59.60	75.70	79.90	84.90	89.10
2016	55	84.72	4.97	66.40	80.90	85.50	88.40	93.00

Summary Statistics: Market Income Per Capita (000s)								
	N	Mean	StDev	Min	25th	Med	75th	Max
Alabama								
2008	37	22.30	5.45	17.07	18.24	21.48	24.14	40.52
2016	37	25.01	5.70	19.25	21.68	23.19	26.30	43.77
Georgia								
2008	37	23.37	4.05	15.18	20.76	22.61	24.93	36.38
2016	37	26.12	6.54	18.90	22.19	24.53	27.64	53.83
Kentucky								
2008	54	15.19	3.43	9.18	13.09	14.92	17.03	25.88
2016	54	17.32	4.07	9.75	14.12	17.63	19.16	27.59
Maryland								
2008	3	25.71	4.27	20.88	20.88	27.30	28.96	28.96
2016	3	30.18	4.16	25.74	25.74	30.82	33.99	33.99
Mississippi								
2008	24	18.09	3.46	12.89	15.47	17.85	19.72	26.73
2016	24	21.44	2.93	17.36	19.69	20.76	22.92	29.25
New York								
2008	14	24.69	2.80	19.01	23.21	23.87	26.98	29.32
2016	14	28.64	2.54	24.43	27.16	28.91	29.91	34.30
North Carolina								
2008	29	22.51	4.42	15.39	19.83	22.23	23.89	32.30
2016	29	24.61	4.70	17.26	21.22	23.03	26.28	36.35
Ohio								
2008	32	20.38	3.22	14.60	18.61	20.51	22.00	30.52
2016	32	24.93	4.55	19.26	22.45	24.21	26.88	41.21
Pennsylvania								
2008	52	23.95	4.02	14.60	21.84	23.39	25.08	38.52
2016	52	29.96	5.00	15.44	26.98	29.17	31.73	44.79
South Carolina								
2008	6	24.01	4.12	18.88	21.41	23.88	24.87	31.13
2016	6	28.19	5.23	20.61	26.28	27.60	30.58	36.45
Tennessee								
2008	52	19.78	4.40	10.36	17.04	19.12	22.12	31.66
2016	52	23.22	5.40	11.95	20.24	22.16	26.20	39.32
Virginia								
2008	25	21.28	4.64	15.40	18.38	20.59	23.48	36.14
2016	25	24.70	6.16	15.03	20.86	23.70	26.60	40.70
West Virginia								
2008	55	20.66	4.62	12.76	17.61	20.15	23.04	32.36
2016	55	22.63	5.60	13.28	18.87	21.85	26.15	36.98

Summary Statistics: Percent of People in Poverty								
	N	Mean	StDev	Min	25th	Med	75th	Max
Alabama								
2008	37	17.48	4.07	7.40	15.50	17.70	19.50	27.40
2016	37	17.62	3.70	8.40	15.10	17.40	20.10	26.00
Georgia								
2008	37	15.67	4.15	6.00	12.60	16.20	18.80	23.00
2016	37	14.95	3.98	5.90	12.60	15.40	17.75	24.80
Kentucky								
2008	54	25.97	6.27	15.00	21.10	25.70	29.60	42.20
2016	54	26.24	6.03	15.60	21.58	25.85	31.85	38.60
Maryland								
2008	3	12.47	2.05	10.40	10.40	12.50	14.50	14.50
2016	3	12.93	3.36	9.70	9.70	12.70	16.40	106.4
Mississippi								
2008	24	23.57	4.85	13.00	20.60	23.60	25.85	35.60
2016	24	21.73	4.58	15.40	17.85	21.65	24.73	30.00
New York								
2008	14	14.13	2.86	8.30	13.30	14.50	16.00	18.80
2016	14	15.47	2.32	10.50	13.98	15.45	17.00	19.60
North Carolina								
2008	29	17.13	3.68	12.20	14.70	16.90	19.20	26.20
2016	29	16.60	3.60	9.50	14.20	16.60	18.05	27.20
Ohio								
2008	32	17.57	4.04	9.30	15.25	17.15	19.45	30.30
2016	32	17.89	4.14	9.50	15.18	17.75	20.28	30.60
Pennsylvania								
2008	52	13.04	2.52	8.30	11.20	13.05	14.75	19.20
2016	52	13.22	2.34	8.30	11.53	13.60	14.48	18.40
South Carolina								
2008	6	16.23	1.88	14.10	14.80	16.20	16.60	19.50
2016	6	16.45	2.88	12.40	14.20	16.35	18.85	20.50
Tennessee								
2008	52	19.41	4.24	11.70	17.00	18.75	22.20	31.50
2016	52	18.62	3.54	11.70	15.98	18.35	21.48	26.70
Virginia								
2008	25	15.78	4.50	5.60	14.50	16.50	18.70	23.80
2016	25	17.09	5.56	8.00	11.85	16.90	20.95	27.70
West Virginia								
2008	55	18.43	4.66	8.40	15.80	18.10	21.00	32.60
2016	55	18.43	4.94	8.50	15.40	17.60	21.70	33.30

Summary Statistics: Unemployment Rate								
	N	Mean	StDev	Min	25th	Med	75th	Max
Alabama								
2008	37	6.37	1.86	3.70	5.10	5.80	7.30	14.40
2016	37	5.98	0.81	4.30	5.50	5.90	6.60	7.60
Georgia								
2008	37	6.39	1.09	4.50	5.70	6.20	7.00	9.80
2016	37	5.33	0.74	4.20	4.70	5.30	5.90	7.10
Kentucky								
2008	54	7.69	1.33	5.50	6.70	7.40	8.30	11.30
2016	54	8.26	2.97	4.20	6.10	8.00	10.20	19.90
Maryland								
2008	3	5.33	0.47	4.80	4.80	5.50	5.70	5.70
2016	3	5.73	0.55	5.20	5.20	5.70	6.30	6.30
Mississippi								
2008	24	8.75	1.77	6.20	7.65	8.20	9.40	13.50
2016	24	6.12	1.13	4.40	5.35	6.05	6.65	8.70
New York								
2008	14	5.85	0.67	4.10	5.60	5.90	6.40	6.90
2016	14	5.49	0.54	4.20	5.10	5.60	5.80	6.30
North Carolina								
2008	29	6.64	1.49	4.70	5.60	6.40	7.70	10.60
2016	29	5.14	0.93	3.90	4.60	4.90	5.40	8.80
Ohio								
2008	32	7.71	1.36	4.90	6.85	7.60	8.60	10.20
2016	32	6.90	1.36	3.60	6.20	6.80	7.55	11.10
Pennsylvania								
2008	52	5.97	0.80	4.30	5.40	6.00	6.30	9.00
2016	52	6.24	0.93	4.20	5.65	6.20	7.05	8.10
South Carolina								
2008	6	6.92	1.25	5.50	6.00	6.80	7.30	9.10
2016	6	4.97	0.60	4.30	4.60	4.85	5.20	6.00
Tennessee								
2008	52	7.77	1.47	5.00	6.65	7.80	8.65	11.50
2016	52	5.62	0.91	4.00	4.80	5.45	6.30	7.90
Virginia								
2008	25	5.24	1.06	3.30	4.40	5.30	5.80	8.00
2016	25	5.73	1.84	3.10	4.80	5.30	6.00	10.80
West Virginia								
2008	55	4.91	1.02	2.80	4.20	4.70	5.50	7.20
2016	55	7.09	2.21	3.40	5.50	6.70	8.50	12.80

Summary Statistics: Transfer Payments Per Capita (000s)

	N	Mean	StDev	Min	25th	Med	75th	Max
Alabama								
2008	37	10.36	1.50	6.24	9.61	10.26	11.36	13.25
2016	37	9.66	1.23	6.65	8.95	9.71	10.49	12.05
Georgia								
2008	37	8.75	1.87	4.35	7.71	8.88	10.07	12.38
2016	37	8.59	1.87	4.54	7.50	8.55	9.74	13.32
Kentucky								
2008	54	12.49	1.96	8.63	11.19	12.22	14.00	16.60
2016	54	12.43	2.09	7.99	10.92	12.15	14.19	17.19
Maryland								
2008	3	11.02	2.22	8.96	8.96	10.72	13.38	13.38
2016	3	10.94	1.59	9.48	9.48	10.72	12.63	12.63
Mississippi								
2008	24	11.66	1.41	9.50	10.55	11.41	12.62	14.36
2016	24	10.42	1.48	7.05	9.83	10.45	10.95	13.10
New York								
2008	14	10.57	1.03	8.53	10.19	10.65	11.34	12.13
2016	14	9.78	1.16	6.46	9.44	10.08	10.59	11.08
North Carolina								
2008	29	10.29	0.96	8.47	9.69	10.41	10.92	12.31
2016	29	10.15	1.23	6.71	9.51	10.36	10.90	12.25
Ohio								
2008	32	10.61	1.53	5.52	10.16	10.82	11.48	12.53
2016	32	10.18	1.51	4.90	9.76	10.36	11.09	12.43
Pennsylvania								
2008	52	10.88	1.30	7.62	10.20	11.04	11.68	13.99
2016	52	10.52	1.27	6.55	9.97	10.64	10.99	13.74
South Carolina								
2008	6	9.89	0.66	8.83	9.73	9.80	10.47	10.72
2016	6	9.07	0.88	7.85	8.55	9.10	9.41	10.42
Tennessee								
2008	52	11.17	1.28	8.71	10.61	10.99	11.85	15.46
2016	52	10.47	1.31	7.79	9.66	10.16	11.18	14.91
Virginia								
2008	25	11.19	1.75	8.12	9.81	11.08	12.44	14.69
2016	25	10.71	1.54	5.63	10.27	10.82	11.48	13.60
West Virginia								
2008	55	11.09	1.92	6.19	10.02	11.23	12.33	15.37
2016	55	10.86	1.78	6.39	9.86	10.95	12.09	14.32