View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by SHAREOK repository

THREE ESSAYS ON BROADBAND ADOPTION

By

JACOB LEE MANLOVE

Bachelor of Arts in Economics
University of Arkansas
Fayetteville, AR
2013

Master of Science in Agricultural Economics
University of Arkansas
Fayetteville, AR
2015

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
May, 2018

THREE ESSAYS ON BROADBAND ADOPTION

Dissertation Approved:

Brian Whitacre

Dissertation Adviser

Dave Shideler

Art Stoecker

Chad Malone

Name: Jacob Manlove

Date of Degree: MAY, 2018

Title of Study: THREE ESSAYS ON BROADBAND ADOPTION

Major Field: Agricultural Economics

Abstract: This dissertation focuses on three issues surrounding broadband internet adoption. The first study examines the recent shift to mobile-only internet connections. The percentage of mobile-only households increased from 9% in 2011 to 20% in 2015, more than doubling in only four years. As this shift continues, it leads to the question of what factors are driving the rise in mobile-only adoption. Using nationally representative data, this study uses logistic regressions and a decomposition technique to understand the trend. The decomposition reveals that a significant portion of the growth was due to an increase in the download speeds of mobile networks. An increased acceptance of mobile-only access by households aged 55 and older was also partly responsible. Understanding (and developing a response to) the trend towards mobile-only adoption will be important as organizations and governments continue to work to close the digital divide.

The second study examines the effectiveness of a well-known grassroots broadband adoption oriented program, Connected Nation. While a large number of studies have examined policies and programs aimed at increasing infrastructure, little analysis to date has focused on evaluating efforts to increase adoption. This analysis focuses on the effectiveness of Connected Nation's efforts by evaluating its impact on adoption rates using a generalized difference-in-difference methodology. While the results indicate there was no significant initial impact, there is evidence of a linear effect resulting in increased adoption 2 to 4 years after the program began. This paper represents a rigorous evaluation of one of the most well-known adoption-oriented programs, and emphasizes that effective use of broadband funds should include empirical analysis of what works.

The third study examines the need for a measure of inequality for broadband adoption. Broadband adoption is primarily measured as the percentage of a population with a connection, regardless of the modality used (i.e. fixed, mobile, or both). This results in a binary measurement that distinguishes between two groups: the percentage that have the defined level of access and those that do not. However, this measure fails to capture differences that may exists in ow users connect – for example, those who use both mobile and fixed versus those use mobile only. This article proposes the use of the absolute value index (AVI) as a measure to study broadband adoption inequality. Using nationally representative data, adoption is broken into four types of connections (none, mobile, fixed, both) to compile the AVI. This measure of inequality may better represent the disparities associated with broadband use across the country, particularly as mobile internet use rises. The results indicate that the AVI can be useful in differentiating adoption patterns (i.e. mobile vs. fixed) in states with similar aggregate levels of adoption. Two nonnested hypothesis tests formally explore the explanatory power of the two measures in explaining economic relationships commonly associated with broadband adoption, and conclude that the AVI does not capture any additional information.

TABLE OF CONTENTS

Chapter Page

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

UNDERSTANDING THE TREND TO MOBILE-ONLY INTERNET CONNECTIONS: A DECOMPOSITION ANALYSIS[1]

Abstract

A growing portion of internet users rely solely on mobile devices such as smartphones for their online access. The percentage of "mobile-only" households increased from 9% in 2011 to 20% in 2015, more than doubling in only four years. As this shift continues, it leads to the question of what factors are driving the rise in mobile-only adoption. Using nationally representative data, this study uses logistic regressions and a decomposition technique to understand the trend. The decomposition reveals that a significant portion of the growth was due to an increase in the download speeds of mobile networks. An increased acceptance of mobile-only access by households aged 55 and older was also partly responsible. Understanding (and developing a response to) the trend towards mobile-only adoption will be important as organizations and governments continue to work to close the digital divide.

Keywords: Decomposition, Internet Adoption, Mobile-only

[1] This paper is published in *Telecommunications Policy* in March 2018. The suggested citation format is Manlove, J. and Whitacre, B. 2018. Understanding the Trend to Mobile-Only Internet Connection: A Decomposition Analysis. *Telecommunications Policy*.

Introduction

As the internet continues to evolve, uneven adoption rates remain across various social and demographic groups (commonly referred to as “digital divides”). Historically, these digital divides have been defined in terms of the percentage of households that do or do not have a fixed, wireline connection (Kayvan, Bahar, & Glenn, 2014; Wodajo & Kimmel, 2013). However, there has been a shift in the digital divide literature to begin looking at other forms of broadband adoption, including mobile connections (Prieger, 2013; Prieger, 2015). Mobile internet connections have risen dramatically as high-speed cellular (i.e. wireless) networks became pervasive. In fact, FCC data from 2014 suggests that nearly 100% of the U.S. population was covered by wireless networks with download speeds of at least 3 megabytes per second (Mbps) (FCC, 2015). As of 2015, an estimated 68% of Americans were reported to have a smartphone with mobile data capabilities (Horrigan & Duggan, 2015). While the percentage of U.S. households accessing the internet solely through a traditional ‘fixed’ connection (such as Digital Subscriber Line (DSL), cable, or fiber) decreased significantly between 2011 and 2015, the share of households connecting through a ‘mobile-only’ connection increased from 8.7% to 20.0% (Figure 1.1).[2] Thus, in only four years, the mobile-only adoption rate has more than doubled. This rapid change in how Americans connect to the internet is striking, and has implications for how organizations and government agencies reach out to their clients and constituents. Multiple researchers have expressed concern that mobile-only access is an inferior way to connect (Reisdorf *et al.*, 2018; Anderson & Horrigan, 2016). In fact, a draft report of the FCC’s 2018 Broadband Deployment Report concludes

[2] For the purposes of this study, a household is defined as mobile-only if their only means of connecting to the Internet is through a paid mobile broadband plan. This plan may be used with any device such as a computer, tablet, cell phone, or smartphone.

that "mobile broadband service is not a full substitute for fixed service (FCC, 2018)." Understanding the mobile-only rise and constructing an appropriate policy response is an important task for the telecommunications field.

A wide array of studies have built the case that broadband adoption – traditionally defined as a fixed, wired connection – can positively affect households and communities (Crandall, Lehr, & Litan, 2007; Whitacre, Gallardo, & Strover, 2014; Whitacre & Manlove, 2016). Less is known about the recent shift to mobile broadband access, including what is driving it and what it means for future broadband policy. This article uses logistic models and a temporal version of the non-linear Blinder-Oaxaca decomposition to better understand the sizeable increase in mobile-only connections between 2011 and 2015. The Blinder-Oaxaca technique decomposes the trend over time into two components: 1) shifts due to changes in the underlying characteristics, such as household demographics or infrastructure availability; and 2) shifts due to changes in the behavioral relationships associated with those characteristics. One possibility is that the demographic makeup of mobile-only adopters changed significantly over the time period in question; or that noticeable improvements to wireless infrastructure across the nation drove the trend. Another possibility is that relationships between specific characteristics and the likelihood of adopting a mobile-only connection shifted during this time. This leads to two questions: 1) are characteristic changes or behavioral changes driving the trend, and 2) which characteristic / behavioral shifts are primarily responsible.

Brief Review of the Literature

Broadband Adoption Determinants and the Rise of the Mobile Network

The drivers of broadband adoption have been well documented in the literature. Household income, age, education and non-metro status are typically found to be the dominant factors in explaining fixed broadband adoption (Hitte & Tambe, 2007; NTIA, 1999, 2002; Whitacre, 2008). Income levels are generally positively correlated with broadband adoption, while older household heads are associated with lower levels of adoption. Similarly, households with high education levels are more likely to be adopters (Quaglione, Agovino, Di Berardino, & Sarra, 2017; Roycroft, 2013), while households in rural areas typically have lower adoption rates than their urban counterparts (Hill, Troshani, & Burgan, 2014). However, it is unclear if these same relationships hold for the adoption of other types of broadband (i.e. mobile). However, Rapport *et al.,* (2004) suggests that the determinants of a mobile connection are consistent with those of a fixed connection.

There has been large growth in the availability of cellular data (i.e. wireless or mobile) networks as smartphones become more prevalent (Xu *et al*., 2011). As the availability and quality of mobile networks increase, households are subsequently provided with a new decision to make regarding their household connection choices. Over the last decade, mobile phones have advanced from providing only voice calls and text messages to becoming a multi-purpose, powerful device also capable of offering internet access. Simultaneously, the internet connection capabilities of mobile networks have also improved, increasing from limited browsing on third-generation (3G) networks (with 3-7 Mbps "peak" download speeds) to the current, more advanced fourthgeneration (4G) (10-25Mbps "peak" download) and long-term evolution (LTE) (40-50Mbps "peak" download) connections capable of providing speeds comparable to a fixed, residential connection (average 2016 home download speed: 55 Mbps) (King, 2016; Kongaut & Bohlin, 2016). In 2015, the Federal Communications Commission (FCC) defined broadband as a connection with a minimum 25 Mbps download speed (FCC, 2015). Given that mobile networks (in particular 4G and LTE) are offering speeds more similar to a fixed, home connection and in line with the FCC definition of broadband; households may now have more options as they consider the cost and benefits of the type of connection they will choose to adopt (mobile-only, fixed-only, both, or no connection).

Mobile Adoption and Substitution of Mobile and Fixed Connections

A recent report by Pew Research on the adoption of broadband found that several demographic groups are more likely to have smartphone-only access (Horrigan & Duggan, 2015). The adoption of smartphones is reaching levels comparable to the percentage of households with a fixed connection, with approximately 65-70% of Americans in each category. The Pew report shows that individuals in rural areas are 6% more likely to connect using only a smartphone in comparison to their urban counterparts. The report also found that income and education matter – but have the opposite relationship with mobile-only adoption than they do for fixed connections. Households with lower income and education levels were *more* likely to have a smartphone as their only means of internet access. Many recent studies have also examined the substitution effect between a mobile and fixed adoption to examine if the two connection types are substitutes or compliments to one another. Cardona *et al.*,

(2009) examined in this substitution effect in the Austrian market and concluded that for private, personal use mobile plans are a substitute for a fixed connection, but for business use the two are compliments. A 2012 study examining broadband adoption in Sweden found similar results, concluding that in most geographic areas mobile broadband was a substitute for a fixed connection (Srinuan, 2012). While the previous two studies determined that mobile plans were indeed substitutes for consumers, two other reports studying the effect in OECD countries found that mobile plans were a compliment to a fixed connection (Lee *et al.*, 2011*;* Wulf *et al.*, 2012). However, the goal of this study is to assess the drivers of the shift to mobile-only adoption in the United States, and study of the substitution effect is left for future research.

Data

To examine the trend in mobile-only adoption, Current Population Survey (CPS) data is used. The CPS is a sample of approximately 50,000 households, and is nationally representative when survey weights are applied. The CPS is administered monthly by the U.S. Census Bureau to collect data for individuals and households pertaining to work, earnings, and education. In addition to the monthly surveys, supplemental surveys are distributed to gain information on a wide array of topics. One such supplemental survey is the Computer and Internet use file which is used to obtain "information about U.S. household access to computers and use of the internet" (Census Bureau, 2011, 2015). This article uses data obtained from this supplemental survey for July 2011 and 2015.

The computer and internet use supplemental file contains a question which asks respondents how their home connects to the internet. Prior to the 2011 version, respondents were presented with only three options to choose from about how they connected to the internet: a regular 'dial-up' telephone connection, other connections (such as DSL, cable, or mobile), or something else. Starting in July of 2011 the choice of connecting to the internet via a mobile-only connection was added as an explicit option. This question (shown below) allows households to be split into various categories of broadband adoption, including those that have a fixed connection, those that have both a fixed and mobile connection, and those that have a mobile-only connection. The choice '*mobile broadband plan*' is defined in the CPS survey as any mobile broadband plan "for a computer, cell phone, smartphone, or tablet". As with all self-reported data, the accuracy is dependent on the household correctly reporting the type of connection they use. In particular, there is some concern that households using a Wi-Fi router to extend a traditional fixed connection may confuse this with having a mobile broadband plan. However, the survey reminds people to "Keep in mind that some people connect in more than one way, especially those with mobile devices such as smartphones." Households who only select "Mobile broadband plan" are the focus of this study.

July 2011 [and subsequent surveys (2013, 2015)]
At home, does anyone in this household access the internet using…
(Select all that apply)
(1) Dial-up service?
(2) DSL service?
(3) Cable modem service?
(4) Fiber-optic service?
(5) Mobile broadband plan?
(6) Satellite service?
(7) Some other service?

Combining the internet connectivity responses with demographic variables from the survey allows for studying what relationships impact the likelihood of having a mobile-only connection, and how these relationships change over time. Demographic variables are available in the CPS data file for each head of household respondent. Table

1.1 displays some basic summary statistics of the variables used to study mobile-only adoption. The demographic composition of mobile-only adopters displayed here compares reasonably well with an alternative sample conducted for PEW internet in 2012. In the PEW sample of 2,300 respondents, 15% of individuals were found to primarily access the internet via a smartphone – which fits into the range of 9% - 20% shown here (Zickuhr & Smith, 2012). Table 1.1 also shows that most mobile-only adopters earn less than $59,999, with smaller percentages in higher income brackets. Those with a graduate degree, bachelors, or some college are much less likely to have only a mobile connection compared to those with a high school education only. Largely, the characteristics do not change significantly over time, although there is an increase in the percentage of older (over 55 years of age) household heads with mobile-only connections.

One characteristic of particular importance that is not fully captured in the CPS data is the broadband infrastructure situation available to each household. The number of fixed providers is obtained from the Federal Communications Commission's Form 477. This form has been used to collect information on the number of providers of broadband services available in counties since 2008 (FCC, 2011, 2015). To capture changes in the wireless infrastructure available to households, county measures of the average wireless download speeds from the National Broadband Map (NBM)[3] are used. Because each household within the CPS cannot be directly matched to a county, the weighted average of fixed providers and wireless download speeds by metro/non-metro county type are

[3] Data collection for the National Broadband Stopped in 2014, as that is the latest available county-level download speeds; it is used as the 2015 measure in this analysis. This time period (2011-2015) corresponds with the rollout of LTE coverage in the USA and the largest portion of the rollout was completed by 2013 (Dano, 2018).

used for each state as a proxy of the network infrastructure to a particular household. This approach has been used in others studies using CPS data (Whitacre and Mills, 2007). The percentage of households served by more than 3 fixed providers rose by 6 percentage points between 2011 and 2015, indicating an increase in the number of fixed providers. There was also significant increase in the speed of wireless networks over the time period as those with access to 10 – 25 Megabits per second (Mbps) increased 42 percentage points and those with access to greater than 25 Mbps increased 10 percentage points. These shifts in infrastructure availability likely contributed to the increase in mobile-only adoption. One characteristic notably missing from Table 1.1 are the prices charged for either a monthly mobile-only connection or a fixed connection. Unfortunately, cost data is not gathered by the CPS or any other reputable national data source; following convention it is no included as a determinant. In fact, a recent paper by Wilson (2017) studying public competition and private investment in internet access finds that prices do not vary significantly. The contribution of each characteristic is assessed using the econometric techniques discussed next.

Methods

Logit Regressions

Previous studies have examined the relationship between household characteristics and the propensity to adopt broadband (and, more generally, the internet). This article builds off of these previous efforts and models the factors impacting a household's choice to adopt a mobile-only connection for 2011 and 2015. As the literature review detailed, income and education levels are positively associated with a household's propensity to adopt a fixed, home broadband connection (Hitt & Tambe, 2007; NTIA, 1999, 2002;

Whitacre, 2008). Households with higher levels of education and income may be quicker to see (and afford) the potential benefits of the technology and thus will be earlier and more frequent adopters of a home connection; however, this relationship may be different for mobile-only adopters.

Logistic regressions are used to uncover the factors that are related to mobile-only adoption for the years 2011 and 2015. For each case, the dependent variable is whether or not the household has only a mobile-only internet connection. The models take the form

(1)
$$y_{ij}^{*} = X_{ij}\beta_j + \varepsilon_{ij}$$
$$y_{ij} = 1 \text{ if } y_{ij}^{*} \geq 0$$
$$y_{ij} = 0 \text{ if } y_{ij}^{*} < 0$$

where y_{ij}^{*} is the latent, unobserved measure of the relative benefits and costs associated with a mobile-only connection for household i in year j; y_{ij} is the observed mobile-only status for household i in year j; X_{ij} is a row vector of demographic and network characteristic variables including income, education, racial/ethnic background, age categories, employment status, a dummy variable for metro vs. non-metro status, a dummy variable for households with access to 3 or more fixed providers, and dummy variables for households with 3 to 4 and 5 or more available wireless providers for the i^{th} household in year j; β_j is the associated parameter column vector, and ε_{ij} is the error term associated with each household and year. This model is first run separately for the years 2011 and 2015. To examine the trends over time, a pooled logistic regression combining the data for 2011 and 2015 data is used. By pooling the data, creating a dummy variable for the year 2015, and interacting each term in X_{ij} with the 2015 dummy, separate parameter estimates for X_{ij} and $(X_{ij} \times 2015)$ can be used to identify how the relationships have changed over time. In particular, statistically significant parameters associated with the vector $(X_{ij} \times 2015)$ indicate that the relationships shifted as time progressed. All specifications of the logistic model used incorporate the CPS survey weights so that the data is nationally representative.

Blinder – Oaxaca Decomposition

One popular method used for examining gaps in means between two groups (in this case mobile-only internet adoption rates over time) is to examine how much of the gap can be explained by differences in observable characteristics and how much is due to changing behavioral relationships between the groups. In this study, such a technique allows for understanding whether the trend to mobile-only is driven by changes in demographics / infrastructure or changes in the way the two groups view the adoption of a mobile-only connection.

To perform the decomposition, two models are estimated (one for each group) and a hypothetical outcome is created where the parameters for one group are combined with the characteristics of the other. This technique is applied with the two groups in question being the individual models for the years 2011 and 2015. This technique of comparing means and decomposing the effects is based on the work of Oaxaca and Blinder (Blinder, 1973; Oaxaca, 1973). Their original model was applicable to linear regressions only, but has since been modified to include non-linear specifications such as the logistic model used here (Nielsen, 1998; Fairlie, 2006). While the initial model was proposed to examine differences in two groups across a single year, it can also be expanded to explain differences across time (Makepeace, Paci, Joshi, & Dolton, 1999; Whitacre, 2010). For the purpose of this article and in the context of the logistic regression in equation (1) the difference in mean probabilities between the two groups, 2011 and 2015, can be expressed as:

(2) $$\left(\hat{P}_{2015} - \hat{P}_{2011}\right)$$

$$= \sum_{i=1}^{N_{2015}} F\left[X_{2015,i}\left(\hat{\beta}_{2015}\right)\right]/N_{2015} - \sum_{i=1}^{N_{2011}} F\left[X_{2011,i}\left(\hat{\beta}_{2011}\right)\right]/N_{2011}$$

where $\hat{P}_{2015}$ and $\hat{P}_{2011}$ are the average probabilities of mobile-only internet adoption for the years 2015 and 2011, respectively, N_{2015} and N_{2011} are the sample sizes for 2015 and 2011, $X_{2015,i}$ and $X_{2011,i}$ are vectors of characteristics for the respective years for each household i, F is the logistic function, and $\hat{\beta}_{2015}$ and $\hat{\beta}_{2011}$ are the estimated parameter estimates for their respective years. Meshing 2011 characteristics with 2015 parameters forms the hypothetical that is necessary, as follows:

(3) $$\hat{P}^0_{2011} = \sum_{i=1}^{N_{2011}} F[X_{2011}(\hat{\beta}_{2015})]/N_{2011}$$

where $\hat{P}^0_{2011}$ is calculated for each household in 2011 and can be interpreted as the probability of adopting a mobile-only connection in 2011 if in fact 2015 parameters were applied. The gap in probabilities can now be written as

(4) $$(\hat{P}_{2015} - \hat{P}_{2011}) = (\hat{P}_{2015} - \hat{P}^0_{2011}) + (\hat{P}^0_{2011} - \hat{P}_{2011}).$$

This allows for the gap in years to be broken down into a component by component basis, one of which is the difference in mean probability associated with *underlying characteristics* $(\hat{P}_{2015} - \hat{P}^0_{2011})$ and the other component which is due to *behavioral changes* associated with the change in years $(\hat{P}^0_{2011} - \hat{P}_{2011})$. Importantly, impacts of specific characteristics as well as behavioral changes can be calculated individually (Cotton, 1988). In order to calculate the contributions from various shifting parameters (behavioral changes), a single parameter from 2011 is replaced with the parameter for 2015 to determine its isolated effect on mobile-only adoption. For example, the contribution of the shifting age parameter can be written as follows:

(5)

$$\frac{1}{N_{2011}}\sum_{1=1}^{N_{2011}}[F(\,INC_{2011}\hat{\beta}_{2011}^{INC}+EDU_{2011}\hat{\beta}_{2011}^{EDU}+\cdots+AGE_{2011}\hat{\beta}_{2011}^{AGE})-$$

$$F(INC_{2011}\hat{\beta}_{2011}^{INC}+EDU_{2011}\hat{\beta}_{2011}^{EDU}+\cdots+AGE_{2011}\hat{\beta}_{2015}^{AGE})].$$

Thus, while parameters for the other characteristics remain the same in both portions of the equation, the parameter for AGE shifts from its 2011 value to its 2015 one. This allows for the estimation of the difference in the probability of mobile-only adoption between 2015 and 2011 that is due solely to parameter changes for a single characteristic. This method is applied to all characteristics used in equation (1) to understand the individual relationships driving the trend to mobile-only adoption. For example, is the shifting relationship between age or race more important in driving the trend to a mobile-only connection? A similar technique can performed for characteristics (i.e. replacing a single trait from 2011 with its value from 2015) to examine which characteristic shifts are important.

Results

Logit Regression Results

The parameter estimates of the logistic regressions for the mobile-only adoption decision are shown in Table 1.2. The first two columns display the results for 2011 and 2015, respectively. The final column displays the results from a pooled sample so that the associated coefficients demonstrate the shift in parameters between the two years.

I first look at the model results for specific years (columns 1 and 2). Generally, higher levels of income exert an increasingly negative effect on the likelihood of mobile-only adoption (relative to the default of <$10,000). This indicates that as income rises (particularly greater than $60,000), households are less likely to be connected to the internet via a mobile-only connection. Relative to the default category of less than a high school degree, education is positively related to mobile-only adoption in 2011 but largely insignificant in 2015. Households in non-metro locations are significantly more likely to have a mobile-only connection in both years. One possible explanation for this is the slower development of wired infrastructure in rural and remote areas, leaving mobile-only as the only viable option for connecting (Kruger & Gilroy, 2016). African-American and Hispanic households were more likely to connect to the internet via a mobile-only connection in both 2011 and 2015, while Asian households were less likely to be mobile-only adopters. Age is negatively related to the adoption of a mobile-only connection, indicating that older households (particularly those aged 55 and older) are less likely to connect to the internet in this way in each of the individual years modeled. Higher numbers of children in the home are associated with an increased probability of connecting through a mobile-only connection. In comparison to households with access to less than 3 fixed providers, those with access to 3 or more are less likely to connect with a mobile-only connection in both 2011 and 2015. This suggests that more fixed providers in an area leads to less mobile-only connections. One explanation of this is that as the number of fixed providers increases, the price of a fixed connection is driven down by increased competition, and fixed access becomes more affordable (Dufwenberg &

Gneezy, 1999). Generally speaking, as available speeds of wireless providers increase, households become more likely to connect with a mobile-only connection.

Using the pooled regression estimates to compare changes over the time period of 2011 to 2015 (Table 1.2), most income parameters are not significantly different between the two years. In terms of education, the relationship between mobile-only adoption and those with some college or higher decreased significantly between 2011 and 2015. This implies that those households with higher education levels became less likely to adopt mobile-only as time progressed. *Ceteris paribus*, this would have resulted in *decreased* levels of mobile-only adoption between 2011 and 2015 – the opposite of what actually happened. Asian and Hispanic households became significantly more likely to adopt mobile-only connections over this time period. Importantly, while the age parameters were still negative in 2015, the relationship dissipated over the time period. The shifting parameter value indicates that older households became more likely to be mobile-only adopters. The parameters for households with access to wireless download speeds of 10 – 25 Mbps saw a dramatic increase, suggesting that households with these levels of speed were more likely to be mobile-only adopters in 2015 (vs. 2011). To understand which of these shifts over time is driving the overall trend, the article returns to the Oaxaca-Blinder decomposition.

Blinder – Oaxaca Decomposition Results

Table 1.3 presents the aggregate results of the decomposition over time. The first row of the table represents the amount of the overall trend explained by changes in the underlying *characteristics*, whereas the second row represents the amount of the overall trend associated with changes in behavioral *relationships* or *responses* to the underlying characteristics. Of the 11.2 percentage point gap between 2011 and 2015, 6.8 percentage points (60.8%) of the increase are explained by the differences in characteristics. Differences to due to behavioral change, account for 4.4 percentage points (39.2%) of the total change. Detailed decompositions are presented in Table 1.4 (characteristics) and Table 1.5 (relationships) by making use of equation [5] to isolate individual mechanisms.

The results in Table 1.4 suggest that of the 11.2 percentage point gap, changes due to the characteristics of the population themselves (i.e. households) are not likely responsible for much of the increased levels of mobile-only adoption. Changes due to income (-2.10%), education (-0.04%), race (0.68%), and other household characteristics (-2.02%) are only minor contributors to the trend.[4] This result suggests that mobile-only adopter demographics did not vary significantly between 2011 and 2015 – a finding supported by the household characteristics in Table 1.1. However, changes in network characteristics (i.e. wireless download speeds) did have a significant impact on the trend. The increase in the percentage of households with access to 3 or more fixed providers between 2011 and 2015 served to lower the likelihood of mobile-only adoption – and hence had a negative impact on the gap. The percentage of households with access to wireless download speeds of 10 – 25 Mbps increased from 0.44 to 0.86 between 2011 and 2015 (Table 1.1), which contributed to roughly 51.19% of the mobile-only adoption rate increase over those years. Similarly the percentage of households with access to wireless download speeds of 25 Mbps or increased as well, accounting for 15.35% of the

[4] Recall that negative contributions reflect the fact that aggregate income levels and education levels slightly increased over time (Table 2.1), suggesting that mobile-only adoption rates would have decreased, *ceteris paribus*. Positive contributions indicate that characteristics positively related to mobile-only adoption increased over time, leading to higher rates.

increase in mobile-only. The increase in wireless download speeds is the single largest driver of the shift to mobile-only, accounting for a total of 66.54% of the total trend.

Alternatively, changes in behavioral relationships between 2011 and 2015 were responsible for 39.2% of the trend as shown in Table 1.3. Table 1.5 suggests that the behavioral responses for age (24.7%) and wireless network speeds (41.2%) are the largest significant behavioral changes driving the trend. Referring back to Table 1.2, the parameters for the age categories became less negative over time. This shift in households aged 35 and older and even more so for those aged 55 or older reflect a growing acceptance of a mobile-only connection and is one the largest behavioral drivers of the trend associated with demographics. The other major behavioral shift is for wireless download speed – particularly those with 10 – 25 Mbps. The behavioral response to the increased wireless download speeds accounts for 41.2% (40.72% + 0.48%) of the trend. On the other hand, the behavioral response to having access to 3 or more *fixed* providers accounted for -2.3% of the gap, indicating that the propensity for mobile-only adoption declined over time in areas with high levels of fixed availability. Shifts in other relationships account for -16.6% of the gap, indicating a negative trend associated with preferences toward mobile-only for characteristics not accounted for in the model. This negative trend could indicate a general aversion for mobile-only, which is just negated by the advances in mobile networks.

Note that behavioral changes for income and education actually decrease the propensity for mobile-only adoption and thus negatively contribute to the trend towards mobile-only. This makes intuitive sense because column 3 of Table 1.2 (pooled regression) suggests that these relationships became more negative over time. So, if characteristics were held constant over time, the lower parameter values would serve to decrease the likelihood of mobile-only adoption. Other shifts in behavioral responses are only relatively minor factors in explaining the trend. Despite this fact, the behavioral changes for age and wireless speed played in significant role in driving the doubling of the mobile-only adoption rate.

Conclusions

This article attempts to model the drivers of the significant increase in mobile-only adoption from 2011 to 2015. Nationally representative CPS data indicates that the adoption of a mobile-only connection increased by 11.2 percentage points during this four-year period. A non-linear decomposition technique demonstrates that largest majority (60.8%) of the trend is accounted for by changes in characteristics, and the remaining portion (39.2%) is accounted for by changes in the relationships between characteristics and mobile-only adoptions. Increases in the download speed of wireless networks accounts for the largest portion of the characteristic change, while a changing responses for age and increased speeds account for the largest portion of the behavioral change.

The results of the behavioral decomposition for demographics reinforce that in addition to low-income households, consideration should also be given to aging households (particularly those over age 55) in developing broadband adoption-oriented policies. As this research showed, shifting preferences among this group are the driving demographic change driving the increase in mobile-only connections. Importantly, this is counter to the commonly-held perception that mobile-only use is being driven by *younger* household heads. This finding also meshes with the results of a recent survey of Detroit residents which suggested that being older increases the risk of being dependent on mobile phones (Reisdorf *et al*., 2018). Companies and organizations reaching out to their constituents online should recognize that older individuals are increasingly accepting mobile-only connections – and in fact are helping to drive that trend.

From a policy standpoint, the most relevant federal program is Lifeline, which helps subsidize the monthly cost of phone and internet plans for low-income households. Lifeline began subsidizing both mobile data plans and fixed broadband connections in 2016 (Lifeline, 2017). However, the current FCC leadership has expressed interest in scaling back the Lifeline program with a proposal to remove non-facilities-based eligible telecommunications carriers (ETCs) (Kastrenakes, 2017). This would essentially eliminate all 3rd-party resellers of the Lifeline service, which are used by the majority of Lifeline mobile data customers. Thus, the proposed Lifeline policy changes would likely reduce the number of mobile broadband subsidies provided to lower income consumers and may counter the trend towards increasing mobile-only adoption.

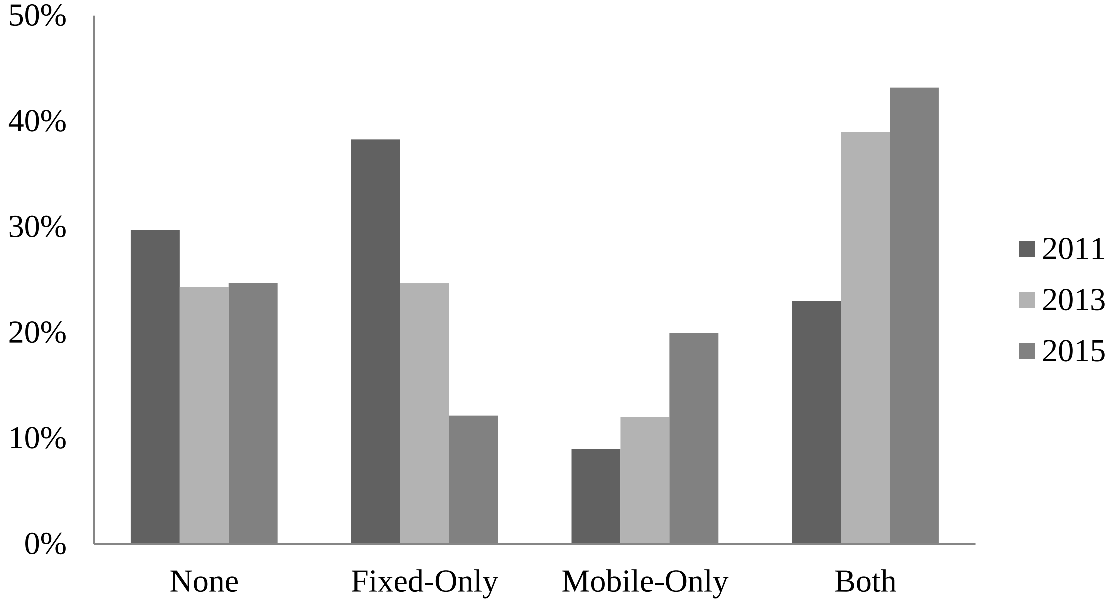
An alternative approach might be for adoption-oriented programs like Lifeline to embrace mobile-only connections and shift towards targeting those that have shown an increase in their willingness to adopt in this way (such as the elderly, Hispanic, or Asians (pulled regression of Table 1.2)). However, more research is still needed to understand the differences between mobile-only and other types of access, and to derive policy solutions with specific internet use goals in mind. While mobile networks may provide Internet access for some households that otherwise might not be able to connect, questions still remain regarding their ability to serve as a pure substitute for a fixed connection. In 2015, 30% of mobile-only adopters report that they frequently reached the maximum data allowance each month which in turn limited their access (Smith, 2015). Mobile adopters reported issues such as a smaller screen size, non-mobile optimized content, and difficulty typing on the phone as the their top three problems that occurred accessing the web on a smartphone (Anderson & Horrigan, 2016). Researchers exploring the digital divide in Detroit expressed skepticism that complex content could be constructed using mobile-only access (Reinsdorf *et al.*, 2018).

In addition to further examination of the degree of substitutability between mobile-only and fixed, home connections, more research is needed to understand if those adopting a mobile-only connection are new internet users. Due to the specific questions asked in the existing CPS surveys, there is no way to assess if households dropped a fixed connection (i.e. "cut the cord") in favor of mobile-only, or if their mobile-only connection is their first attempt at gaining internet access. Households cutting-the-cord with a fixed, home connection - and switching to no internet connection - cite reasons of costs, lack of need, and inadequate computers (Whitacre & Rhinesmith, 2015). Understanding the rationale of cord-cutters who switch to mobile-only access would be an important data point, particularly in conjunction with information regarding the substitutability between the two.

Regardless, understanding the mobile-only trend is important for shaping future iterations of policy as organizations seek to maximize their efforts surrounding broadband adoption and usage. Many advocacy groups have an explicit focus on attempting to shrink the digital divide, and the results here provide some guidance about their road forward. For example, digital inclusion advocates often offer workshops and learning exercises for individuals with limited internet experience (NDIA, 2018).

Recognizing (and responding to) the trend towards mobile-only use will be important as they reach out to their constituents. Their leadership will need to make a decision about whether they embrace the mobile-only shift (and provide training focused on this modality / encourage more mobile adoption), or instead push back and emphasize the importance of what can be done with a fixed connection.

Figure 1.1. Household Internet Connection Type by Year



Source: CPS Computer and Internet Use Supplements, 2011, 2013, 2015

Table 1.1. Household Characteristics
Summary Statistics of Mobile-Only Adopters

Characteristic	2011	2015
Mobile-Only Adopters	8.73%	19.96%
Income		
Less than $10,000 - $29,999	0.339	0.311
$30,000 - $59,999	0.293	0.283
$60,000 - $99,999	0.206	0.213
$100,000 - More than $150,000	0.161	0.193
Education		
High School	0.336	0.335
Some College	0.164	0.165
Bachelor	0.140	0.144
Graduate Degree	0.059	0.061
Race		
Black	0.107	0.118
Asian	0.039	0.044
Hispanic	0.100	0.114
Non-Metro Status	0.215	0.206
Age		
Less than 35	0.339	0.329
35 to 54	0.281	0.261
55 or More	0.380	0.410
Number of Children in Home	0.365	0.332
Retired	0.200	0.217
Employed	0.521	0.520
Unemployed	0.056	0.033
Infrastructure Availability		
Number of Fixed, Wired Providers		
0 to 3 Providers	0.540	0.476
More than 3 Providers	0.460	0.524
Wireless Download Speeds		
Less than 10 Mbps	0.545	0.026
10 - 25 Mbps	0.439	0.856
More than 25 Mbps	0.016	0.118
No. Observations	52,981	50,280

Source: Current Population Survey, Computer and Internet Use Supplements, 2011, 2015; FFC Form 477, 2011, 2015; National Broadband Map, 2011,2014

Table 1.2. Logit Results by Year for Mobile-Only

Variable	2011		2015		Changes from 2011 - 2015	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Income						
$10,000 - $19,999	-0.042	0.061	-0.018	0.052	0.025	0.080
$20,000 - $29,999	0.136	0.057**	0.033	0.051	-0.103	0.077
$30,000 - $39,999	0.041	0.059	0.045	0.052	0.004	0.078
$40,000 - $49,999	0.053	0.064	-0.046	0.056	-0.099	0.085
$50,000 - $59,999	-0.050	0.065	-0.047	0.056	0.004	0.086
$60,000 - $74,999	0.123	0.100	-0.108	0.054**	-0.232	0.114**
$75,000 - $99,999	-0.106	0.061*	-0.172	0.053***	-0.066	0.081
$100,000 - $149,999	-0.241	0.065***	-0.265	0.055***	-0.025	0.086
More than $150,000	-0.233	0.076***	-0.341	0.060***	-0.108	0.097
Education						
High School	0.055	0.041	0.043	0.028	-0.012	0.050
Some College	0.284	0.046***	0.038	0.035	-0.246	0.058***
Bachelor	0.098	0.054*	-0.037	0.039	-0.135	0.067**
Graduate Degree	0.360	0.072***	-0.054	0.055	-0.414	0.091***
Race						
African-American	0.277	0.048***	0.258	0.034***	-0.019	0.059
Asian	-0.366	0.092***	-0.102	0.058*	0.264	0.109**
Hispanic	0.041	0.053	0.259	0.035***	0.219	0.063***
Non-Metro Status	0.073	0.048	0.218	0.038***	0.146	0.062**
Age						
34 to 54	-0.469	0.036***	-0.119	0.028***	0.350	0.046***
55 or More	-1.006	0.051***	-0.385	0.033***	0.620	0.061***
Number of Children in Home	0.063	0.016***	0.029	0.013**	-0.035	0.021
Retired	-0.328	0.072***	-0.342	0.043***	-0.014	0.084
Employed	0.206	0.037***	0.169	0.027***	-0.037	0.046
Infrastructure Availability						
3 or More Available Fixed Providers	-0.253	0.060***	-0.318	0.055***	-0.065	0.081
Wireless Download Speeds						
10 - 25 Mbps	-0.137	0.063**	1.083	0.265***	1.220	0.273***
More than 25 Mbps	0.921	0.187***	1.321	0.269***	0.399	0.328
Constant	-1.996	0.067***	-2.215	0.265***	-0.218	0.273
No. Observations	52,981		50,280		103,261	
Pseudo R^2	0.045		0.043		0.067	

*, **, *** represent statistical significance at the p=0.10, 0.05, and 0.01 levels, respectively.

Table 1.3. Decomposition of Trend to Mobile-Only

	Coefficient	SE	Relative %
Contributions Due to Differences in Characteristics	0.068	0.013***	60.80%
Contributions Due to Differences in Behavior	0.044	0.014***	39.20%
2015-2011 Adoption Gap	0.112		
No. Observations	103,261		

*, **, *** represent statistical significance at the p=0.10, 0.05, and 0.01 levels, respectively.

Table 1.4. Decomposition of Trend to Mobile-Only: Differences Due to Characteristics

Variable	Coefficient	SE	Relative %
Income			
$10,000 - $19,999	0.00003	0.000077	0.02%
$20,000 - $29,999	-0.00004	0.000058	-0.03%
$30,000 - $39,999	-0.00003	0.000029	-0.02%
$40,000 - $49,999	0.00001	0.000016	0.01%
$50,000 - $59,999	0.00002	0.000023	0.02%
$60,000 - $74,999	-0.00099	0.000504*	-0.88%
$75,000 - $99,999	-0.00010	0.000032***	-0.09%
$100,000 - $149,999	-0.00044	0.000096***	-0.39%
More than $150,000	-0.00082	0.000153***	-0.73%
Education			
High School	0.00000	0.000001	0.00%
Some College	0.00000	0.000002	0.00%
Bachelor	-0.00002	0.000018	-0.02%
Graduate Degree	-0.00002	0.000019	-0.02%
Race			
African-American	0.00037	0.000054***	0.33%
Asian	-0.00006	0.000035*	-0.06%
Hispanic	0.00046	0.000069***	0.41%
Non-Metro Status	-0.00027	0.000043***	-0.24%
Age			
34 to 54	0.00029	0.000071***	0.26%
55 or More	-0.00140	0.000146***	-1.25%
Number of Children in Home	-0.00012	0.000058**	-0.11%
Retired	-0.00075	0.000104***	-0.67%
Employed	-0.00001	0.000002***	-0.01%
Infrastructure Availability			
3 or More Available Fixed Providers	-0.00256	0.000450***	-2.28%
Wireless Download Speeds			
10 - 25 Mbps	0.05748	0.010724***	51.19%
More than 25 Mbps	0.01724	0.002534***	15.35%

*, **, *** represent statistical significance at the p=0.10, 0.05, and 0.01 levels, respectively.

Table 1.5. Decomposition of Trend to Mobile-Only: Differences Due to Behavior

Variable	Coefficient	SE	Relative %
Income			
$10,000 - $19,999	0.00027	0.000877	0.24%
$20,000 - $29,999	-0.00114	0.000852	-1.01%
$30,000 - $39,999	0.00004	0.000798	0.03%
$40,000 - $49,999	-0.00074	0.000638	-0.66%
$50,000 - $59,999	0.00003	0.000643	0.02%
$60,000 - $74,999	-0.00056	0.000278**	-0.50%
$75,000 - $99,999	-0.00061	0.000756	-0.54%
$100,000 - $149,999	-0.00020	0.000713	-0.18%
More than $150,000	-0.00059	0.000540	-0.53%
Education			
High School	-0.00036	0.001447	-0.32%
Some College	-0.00346	0.000830***	-3.08%
Bachelor	-0.00162	0.000807**	-1.45%
Graduate Degree	-0.00207	0.000463***	-1.84%
Race			
Black	-0.00017	0.000538	-0.15%
Asian	0.00089	0.000369**	0.79%
Hispanic	0.00186	0.000552***	1.66%
Non-Metro Status	0.00268	0.001113**	2.39%
Age			
34 to 54	0.00840	0.001142***	7.48%
55 or More	0.01934	0.001924***	17.23%
Number of Children in Home	-0.00108	0.000680	-0.96%
Retired	-0.00024	0.001448	-0.22%
Employed	-0.00166	0.002062	-1.48%
Infrastructure Availability			
3 or More Available Fixed Providers	-0.00257	0.003228	-2.29%
Wireless Download Speeds			
10 - 25 Mbps	0.04572	0.008624***	40.72%
More than 25 Mbps	0.00054	0.000427	0.48%
Constant	-0.01866	0.022698	-16.62%

*, **, *** represent statistical significance at the p=0.10, 0.05, and 0.01 levels, respectively.

CHAPTER II

AN EVALUATION OF THE CONNECTED NATION BROADBAND ADOPTION PROGRAM

Abstract

Closing the digital divide and increasing broadband adoption within households and communities continues to be a target for both government and nonprofit groups. While a large number of studies have examined policies and programs aimed at increasing infrastructure, little analysis to date has focused on evaluating efforts to increase adoption. One of the most well-known programs focused on adoption is Connected Nation which partnered with 12 states and provided local curricula aimed at closing the digital divide through increased adoption. This analysis focuses on the effectiveness of Connected Nation's efforts by evaluating its impact on adoption rates using a generalized difference-in-difference methodology. While the results indicate there was no significant initial impact, there is evidence of a linear effect resulting in increased adoption 2 to 4 years after the program began. This paper represents a rigorous evaluation of one of the most well-known adoption-oriented programs, and emphasizes that effective use of broadband funds should include empirical analysis of what works.

Keywords: Broadband, Connected Nation, Generalized Difference-in-Differences

Introduction

The number of households connecting to the internet – particularly high-speed internet - has increased dramatically since the early 2000s. As shown in Figure 2.1, the broadband adoption rate has steadily increased since 2000, plateauing near 70% in 2015[5]. Despite this upward trend, there still remain gaps in adoption (commonly referred to as 'digital divides') among various sociodemographic and geographic groups. Increasing broadband adoption and closing these digital divides is a common goal of both government and non-profit groups (FCC, 2017). The scientific literature has shown that both increased broadband availability and adoption – generally defined as a fixed, wired connection – can positively impact households and communities (Crandall, Lehr, & Litan, 2007; Czernich et al., 2011; Kandilov & Renkow, 2010; Whitacre, Gallardo, & Strover, 2014; Whitacre & Manlove, 2016). However, most studies evaluating broadband policy focus on efforts to increase infrastructure (Dinterman & Renkow, 2017). Little analysis to date has focused on evaluating efforts to increase broadband adoption.

One of the most well-known 'grassroots' programs focusing on increasing broadband availability and adoption is Connected Nation. This program, which originally started in Kentucky in 2004 (as "Connect Kentucky"), is most well-known for working with local broadband providers and community stakeholders to create detailed maps of areas within states that are underserved by broadband (Connected Nation, 2018a). The Broadband Data Improvement Act passed by Congress in 2008 as part of the American Recovery and Reinvestment Act (ARRA) specifically promoted this type of public-private partnership for improving broadband availability and increasing adoption rates.

[5] The FCC defines a broadband connection has having 25 Megabytes per second (MBPS) download speeds or faster. (FFC, 2015)

ARRA provided funding to states for mapping broadband availability, and also funded some efforts associated with increasing adoption (NTIA, 2015). Under the ARRA legislation, each state was responsible for selecting an entity to construct detailed broadband availability maps of served (and underserved) areas. Twelve states chose Connected Nation as their broadband mapping service. While best known for the maps they generate and their ability to bring relevant providers to the table, a large part of the program's work focuses on increasing broadband adoption. The adoption-oriented programs administered by Connected Nation include "Get Connected," which emphasizes gathering technology advocates in an area to evaluate the current state of broadband adoption and use; providing digital training opportunities to help those lacking basic computer and web browsing skills; and "Computers 4 Kids", which provides technology support to vulnerable children.

As of 2017 there were 14 states, including states which did initially select Connected Nation under ARRA, participating in the Connected Nation effort. Although states are considered partners, the work is typically performed at the county level. Program participation at the county level is primarily driven by participant ambition, with counties reaching out to Connected Nation expressing a desire to improve their broadband adoption. In addition to infrastructure, each participating county emphasizes (to varying degrees) broadband awareness and technology training in an effort to promote broadband adoption (Connected Nation, 2018b). Current broadband policy investments focus primarily on improving infrastructure, and as such much of the literature is focused on the economic outcomes associated with increases in broadband availability (Kim & Orazem, 2017; Kandilov & Renkow, 2010). The existing literature on the effectiveness of broadband adoption-oriented programs is limited, and generally finds no significant increases in adoption due to such programs (Hauge & Prieger, 2015; LaRose et al., 2014). However, the Connected Nation program has not been rigorously evaluated to date. It is important to evaluate the success of adoption-oriented programs so that resources can efficiently be used to increase adoption. This analysis focuses on the effectiveness of Connected Nation's programs in increasing broadband adoption using a generalized difference-in-differences (GDD) methodology.

Literature

Community Impacts of Broadband Adoption

Broadband adoption, rather than availability (infrastructure) alone has been found to have many positive effects at the community level. Increases in adoption rates have been found to lead to economic growth (Holt and Jamison, 2009; Crandall et al., 2003). Other studies find that in rural areas increased adoption is associated with positive impacts on the number of firms, unemployment, and median household income (Whitacre et al., 2014a, Whitacre et al., 2014b). A study examining the relationship between civic engagement and broadband adoption found that communities with higher levels of adoption tend to be more civically involved – for example by being more willing to contact a government official or participate in community groups (Whitacre & Manlove, 2016). In light of these studies, adoption-oriented programs should be supported, but the effectiveness of such programs should be evaluated.

Approaches to Broadband Adoption Programs and Factors Affecting Non-adoption

A large body of literature exists on the determinants of broadband infrastructure and adoption. The search of literature on the topic is limited to research which directly seeks to evaluate program outcomes as well as those that highlight both the direct and indirect factors driving broadband adoption. According to the Federal Communication Commission's (FCC) report 'Broadband Adoption and Use in America,' the three primary reasons why 35% Americans are non-adopters of broadband are cost (36%), digital literacy (22%), and lack of relevance to daily life (19%) (J.B. Horrigan, 2010). The goals of the Connected Nation program align closely with all three of these primary reasons by working to increase subscription affordability, increase digital literacy, and educate users on the relevance of broadband. Hauge and Prieger (2010) reviewed demand-side (adoption and use) oriented programs aimed at increasing broadband adoption, and concluded that these programs work best when both supply and demand issues related to increasing adoption are used. Their paper notes that "Encouraging broadband adoption is only part of a larger digital literacy effort, and programmes work when they make nonusers want to connect, make the Internet cheaper and easier to use, and adjust to users' preferences" (pp.25). Surveying previous works on the topic, a 2010 study affirms the multifaceted approach to increasing broadband adoption by suggesting efforts to change and adjust user preferences, while attempting to increase affordability (Turner-Lee & Grant, 2010).

The primary method used to encourage broadband uptake amongst historically low-adopting groups is through providing support at the local level through education and training programs. Research on 'digital divides' or differences in adoption patterns for demographic groups, specifically race, age, and ethnicity, has shown large statistically significant gaps that do not seem to be driven simply by the availability of infrastructure (Prieger, 2010). As such, many broadband adoption-oriented programs work directly with these vulnerable groups by providing educational, demand-side programs (Prieger, 2015). For example, the National Digital Inclusion Alliance (NDIA) works at the local level to address issues of non-adoption (NDIA, 2018). A 2010 article using data from the National Minority Broadband Adoption Study provides evidence that the value of a broadband connection is different among racial and ethnic groups and is subsequently a driving factor of many digital divides (Gant, Turner-Lee, Le, & Miller, 2010). A recent study by Reisdorf et al. (2018), suggests that low income households do recognize the important of a connection, but are unable to afford it. Similarly, having access to a network of social support for potential adopters is found to be crucial for providing meaningful impact on the perception and meaningfulness of the internet and thus increased adoption (John B. Horrigan & Scatterwhite, 2010; Sweeney & Rhinesmith, 2016). In addition to lack of social support structures related to broadband adoption, lack of content relevant to non-adopters is cited as a potential reason for lower adoption rates. Peronard and Just (2011) suggest that optimizing content to issues relevant to non-adopters may potentially increase adoption, although the research does not link this method to any current program. A 2013 study reviewing policies related to broadband adoption across various countries concluded that no one broadband adoption program is universally optimal for all situations and countries. This study cites the three core areas of a successful broadband adoption program to be 1) supply, 2) demand, and 3) developing human capabilities components (Martyn, 2013).

In addition to the programs mentioned above which focus on awareness, many programs exists which provide subsidies to help low-income households to connect. One of the most well-known subsidy programs available in the United State is Lifeline which provides subsidies for both mobile and fixed broadband plans (Lifeline, 2018). However, this program is being scaled back by current administration (Kastrenakes, 2017). Many providers also provide reduced rates for services to low income households which are typically awarded based on the households Supplemental Nutrition Assistance Program (SNAP) or National School Lunch Program eligibility (EveryoneOn, 2018; Whitacre, 2017). No research exists on these programs and their effect on increasing broadband adoption.

Evaluation of Broadband Programs

The most studied broadband program is the ARRA's Broadband Technology Opportunities Program (BTOP) which invested $4.7 billion over the period of 2009-2013 to increase broadband access and adoption. While the largest part of the fund went to increasing infrastructure ($3.5 billion), $251 million were used for sustainable broadband adoption projects (NTIA, 2015). Several of the papers studying the effect of the adoption-oriented projects report no statistically significant impact on increasing adoption. The mismanagement of fund distribution for the BTOP program was also cited as the primary reason for the programs lack of success. Previous research reports that funds for the program were poorly geographically distributed in comparison with the areas with the most need (Gimpel, Lee, & Thorpe, 2012; Rosston & Wallsten, 2013). In addition to these works focused on the distribution of funds, several other recent studies attempted to empirically measure the effect of BTOP on broadband adoption rates.

The National Telecommunications and Information Administration (NTIA) selected ASR Analytics to perform an evaluation of the BTOP program (NTIA, 2013). The ASR report used matching and difference-in-difference techniques to study the social and economic impacts of the program. While the ASR report found significant increases in infrastructure *availability* for communities receiving BTOP funding, the program's effect on increasing adoption were not rigorously studied (ASR, 2014). LaRose et al. (2014) examined the distribution of the BTOP funds and found empirical evidence to suggest a correlational relationship between fund distribution and adoption rates. However, this analysis did not control for the increasing trend in broadband adoption (Figure 2.1) across the population at large and as such the results offer limited evidence on the causal impact of the program. Hauge and Prieger (2015) extended the evaluation of BTOP and its effects by controlling for the general, positive trend of broadband adoption over the same time period of the program using a fixed effects model. After controlling for the trend, they conclude that BTOP had no significant impact on increasing the adoption of broadband.

Connected Nation has conducted internal analysis on the efforts of their program. These reports generally find that states and counties participating in the program experienced an increase in broadband adoption rates. However, similar to the analysis of La Rose et al., the trend of increasing broadband adoption is excluded from the analysis and thus provides little evidence on the effectiveness of the program (Connected Nation, 2018c).

Data and Methods

The recent program evaluation literature focuses on several techniques that may be used to tease out causal impacts of a specific intervention. These include propensity score matching (PSM), synthetic control, and difference-in-differences. PSM matches treated units to otherwise similar units to assess the causal treatment effect, but requires a strong set of covariates to achieve balance between the treated and control groups (Caliendo and Kopeinig, 2008). Due to the lack of available covariates at the county-level to achieve balance in the matching, this method was deemed inappropriate for this analysis. Synthetic control methods provide an estimate of the treatment effect by synthetically creating a control group composed of multiple comparison units to compare the treated group to. Synthetic control requires ample pretreatment periods from which to create the control (Abadie et al., 2010). As described in the FCC data section below, adequate pretreatment data does not exist for this methodology. The technique used for this analysis, generalized difference-in-difference (GDD) requires panel data containing observations on individuals (counties) observed over multiple periods of time to assess the impact of the treatment (Connected Nation Program) on the outcome variable (broadband adoption). To control for other factors influencing broadband adoption over the same time period, time-varying county-level demographic information is also used. The GDD methodology is most appropriate for this analysis and allows for the effectiveness of the program to be evaluated using the current data while exploiting within time and group variation to control for factors influencing adoption.

Connected Nation Data

The Connected Nation program has provided data on eight of the states they have worked with in the past, including the dates when each county in those states began the process. Given the availability of the FCC's county-level adoption data from 2008 - 2016, a natural experiment opportunity arises: assess whether counties that went through the program during those years experienced subsequently higher levels of broadband adoption than those that did not. A county is defined as a participant (treated) if they were active in the program for more than 6 months of the year in question. The typical Connected Nation program ranges from 6 to 9 months to complete, with monthly community meetings during this time. Similarly, in order to assess the potential long-term impact of the program a county is defined as remaining in the treatment group regardless of how long the Connected Nation program was active. In addition to the binary indicator of program participation described above, the specification also includes a variable for the number of years since the program initially began. This allows for testing of incremental increases in broadband adoption after completion of the Connected Nation program – perhaps the grassroots effort takes time to build up. The analysis is restricted to only counties which started the program in 2012 or later to allow for adequate pre-treatment periods for the analysis. This restriction includes 71 counties [Iowa (52), Michigan (7), Nevada (7), South Carolina (1), Texas (4)] that received treatment in 2012 and an additional 20 counties [Iowa (2), Michigan (2), Nevada (6), South Carolina (6), Texas (4)] receiving treatment in 2013. Figure 2.2 shows the participating counties, and the resulting change in broadband adoption 2 years after the program began. Of the 71 counties treated in 2012, 28 (39.4%) experienced an increase in adoption 2 years after the program and of the 20 treated in 2013, 7 (35.0%) had increased adoption.

FCC County Level Broadband Adoption Data (Form 477)

The FCC has provided categorical county-level data on household adoption rates as well as the number of providers available for residential, fixed (wired) connections on an annual basis since 2008. The broadband adoption data provided by the FCC is split into 5 categories which are based on the proportion of households that connect with a high-speed (defined as 200 kilobytes per second (kbps) or higher) connection[6]: 0-19.9% adoption, 20-39.9% adoption, 40-59.9% adoption, 60-79.9% adoption, and 80-100% adoption. While the categorical nature of the data does result in loss of information regarding the specific percentage of households adopting, it still serves as a useful measurement for assessing trends in adoption. When there are 5 or more categories in the interval set, treating the variables as continuous for the purpose of analysis has been shown to pose no significant threat to the validity of regressions results (Johnson & Creek, 1983; Zumbo & Zimmerman, 1993). Figure 2.3 presents the average adoption level over the time period by treatment group. The treatment group in Figure 2.3 includes all 91 counties that received treatment regardless of when the treatment began, while the untreated group includes all 2,808 counties used as the control[7]. Generally, counties receiving treatment have lower levels of adoption than those not part of the Connected Nation program. This is consistent with the idea of self-selection bias (i.e. counties with low adoption are more likely to participate) and the need for an evaluation technique that

[6] Note that this speed is different than the current FCC definition of broadband which is currently defined as a minimum 25 megabytes per second (mbps) download (FCC. 2015).
[7] Other Connected Nation participant counties (Ohio and Tennessee) were excluded from the analysis since they the program too early to establish a baseline trend (2009 and 2010 start dates).

control for this possible bias. This data can easily be meshed with other county-level data sources such as demographic data provided by the Census or Bureau of Economic Analysis (BEA). Broadband price data is not included in the analysis due to the lack of county-level estimates of prices. While the important of broadband price data is recognized, there is no evidence of relevant data being collected other than the internet price index from the Bureau of Labor Statistics (Donnellan, 2017; Molnar et al., 2014).

Demographic Data

For the purpose of this analysis, the FCC adoption data is meshed with basic demographic information (population, income, poverty, and unemployment) to control for other factors related to broadband adoption. Summary statistics for treated and untreated counties are shown in Table 2.1. County population data is included to account for the varying populations across the treated and untreated groups; counties chosen for the Connected Nation program have significantly smaller populations than those not participating. Previous literature cites income and education as two of the primary drivers of broadband adoption. Generally, households with higher income levels are more likely to be broadband adopters (Hill, Troshani, & Burgan, 2014; Quaglione, Agovino, Di Berardino, & Sarra, 2017). Annual county-level income estimates are provided by the BEA. Similarly to income, higher levels of education are associated with higher levels of broadband adoption (Roycroft, 2013; Quaglione, Agovino, Di Berardino, & Sarra, 2017). While the American Community Survey (ACS) does provide estimates of educational attainment, it does so with 5-year estimates. The ACS cautions against interpolating this data to yearly values, and as such poverty and unemployment levels as a proxy for this variable (Bureau, 2009). Data for poverty and unemployment come from the Census

Small Area Income and Poverty Estimates and Bureau of Labor Statistics Local Area Unemployment, respectively. It is expected that poverty and unemployment will have a negative relationship with broadband adoption levels.

Difference-in-Difference Methods

The original difference-in-difference (DD) estimator from the work of Ashenfelter and Card (1985) provides the foundation of the analysis for this paper. Their model is set up so that outcomes are observed for two groups over two time periods where one group is exposed to a treatment in the second period but not the first. The second group is not exposed to the treatment in either period. The effect of the treatment is then defined as the difference between the average gain in the control and the average gain in the treatment group. Differencing the data removes any biases from permanent differences between groups, as well as biases from comparing groups across time. The difference-in-difference estimator has since been expanded to allow for treatments occurring over multiple time periods (Bertrand, Duflo, & Mullainathan, 2004). The generalized difference-in-difference (GDD) estimator is estimated as a two-way fixed effects model controlling for within time and group variation.

The assumptions of the DD estimator are also required for the GDD estimator so that the technique provides an unbiased, consistent estimate of the treatment effect. The three assumptions that must be true are: 1) the model is correctly specified and the covariates included are correct, 2) the error term has expectation of zero and is independent of the covariates, and 3) the treatment group and the control will follow the same trend over time in the absence of treatment (Li, Graham, & Majumdar, 2012). This last requirement is commonly referred to as the parallel trend assumption. To address the parallel trend assumption in GDD, one approach to assure the treated and untreated groups follow a common trend is to examine the data graphically. Referring back to Figure 2.3 and observing the adoption trend between 2008 and 2011 (pre-treatment), it is reasonable to assume the two groups follow a relatively common trend. In addition to graphical analysis, Abadie (2005) suggests that covariates can be introduced to the GDD model to account for factors that could lead to violations of the parallel trend assumption.

This analysis provides several specifications of the generalized difference-in-difference model to evaluate the effectiveness of the Connected Nation program on broadband adoption. The analysis begins by estimating the following model under the assumption that counties were not individually selected for treatment, but rather because included because the state chose to be a participant. Thus, this specification controls for fixed effects at the state-level:

(1) $$Adopt_{ist} = \alpha_s + \delta_t + \gamma(CN)_{it} + X_{it}\beta + \varepsilon_{ist}$$

where $Adopt_{ist}$ is the level of adoption, *i* indexes the county, *t* indexes the year, *s* indexes the state, and CN_{it} is an indicator for whether county *i* was a Connected Nation participant in year *t.* All specifications include a full set of year indicators (δ_t) and indicate in the results when a full set of state indicators (α_s) as well time-varying county-level variables (X_{it}) are included. The vector X_{it} includes county population, per capita income, unemployment, and poverty. The variable γ is the average effect of the Connected Nation program on broadband adoption. To test for a possible linear effect of the program the following model is also estimated:

(2) $$Adopt_{ist} = \alpha_s + \delta_t + \gamma(CN)_{it} + \eta(Years\ in\ Program)_{it} + X_{it}\beta + \varepsilon_{ist}$$

including $Years\ in\ Program_{it}$ which is a discrete variable for the number of years since county i began the Connected Nation program. A positive and significant η would suggest a positive linear effect of the program over time. To evaluate the overall effect of the trend under this specification, the impact of the program is calculated as $\gamma + \eta(Years\ in\ Program)$. Standard errors for both models are calculated using a Huber-White robust variance matrix that allows for clustering at the state-level.

Relaxing the assumption that states are systematically selected for participation, but rather selection occurs at the county-level, the following model is estimated:

(3) $$Adopt_{it} = \alpha_i + \delta_t + \gamma(CN)_{it} + X_{it}\beta + \varepsilon_{it}$$

including a full set of indicators for county (α_i). Similar to the methods used in equation 2, $Years\ in\ Program_{it}$ is included to test for linear trends of the program on broadband adoption when grouping at the county-level:

(4) $$Adopt_{it} = \alpha_i + \delta_t + \gamma(CN)_{it} + \eta(Years\ in\ Program)_{it} + X_{it}\beta + \varepsilon_{it}.$$

As with models 1 and 2, it is indicated in the results when a full set of county indicators and time-varying covariates are included. Standard errors for both models 3 and 4 are calculated using a Huber-White robust variance matrix that allows for clustering at the county-level.

Results

The model specifications for the effect of the Connected Nation program on broadband adoption are presented in Tables 2.2 and 2.3 which control for state and county fixed effects, respectively. The top row of the tables present the estimates of the average effect of the program. Models 4 and 5 of both tables include an additional estimate of the possible linear trend of the program. Both estimates are followed by their cluster-robust standard errors and associated p-value.

The estimated effect of the program for the models which controlled for state-level fixed effects are presented in Table 2.2. The first model (1) controlled for only program and fixed effects for time and found the estimated average effect of the program was insignificant. Models 2 and 3 introduce state fixed effects - one with time-variant covariates- and similarly report no significant effect of the program. The linear effect of the program is introduced in models 4 and 5. Both models find an initial, negative effect of the program followed by a positive trend. The initial and linear effect of the trend were tested for joint significance and found to be significant for both models 4 and 5 with test p-values of 0.000 and 0.007, respectively. Following this trend (using model 4), the effect of the program would become positive four years after the initial treatment.[8] The time varying covariates when used (models 3 and 5) behaved as expected. Population and per capita income were positively related to greater adoption, indicating that counties that are larger and have higher income are more likely to have higher levels of adoption. Both poverty and unemployment were negatively related to adoption suggesting that counties with high poverty and unemployment are less likely to be high adopters of broadband.

[8] $\text{Year 4: Total Effect} = -0.166 + 4(0.047) = 0.022$

The full regressions including covariates and time fixed effects are available in Appendix 2A.

The estimated program effects when controlling for county-level fixed effects are presented in Table 2.3. As indicated by the higher adjusted R^2 values, the county-level models capture a larger portion of the variation in adoption rates. The first model again is the naïve model without controlling for any location (county-level) fixed effects. Models 2 and 3 indicate a positive but insignificant effect of the program on broadband adoption. The possible linear effect of the program is introduced again in models 4 and 5. While these models indicate no significant initial impact of the program, there is a positive significant trend beginning in year 2. The initial impact of the program becoming insignificant is reflective of the county-level regression capturing more variation on the data with group fixed-effects. The joint significance of the program effect and the yearly effects are insignificant when tested jointly with an F-test having p-values of 0.842 and 0.888, respectively. However, following the work of Kass and Raftery (1995), the BIC of model 5 (linear trend included) exhibited a change of greater than two compared to model 4 indicating strong evidence for inclusion of the linear trend. When included, the time varying covariates performed similar to the models with state fixed effects (Appendix 2B).

Conclusions

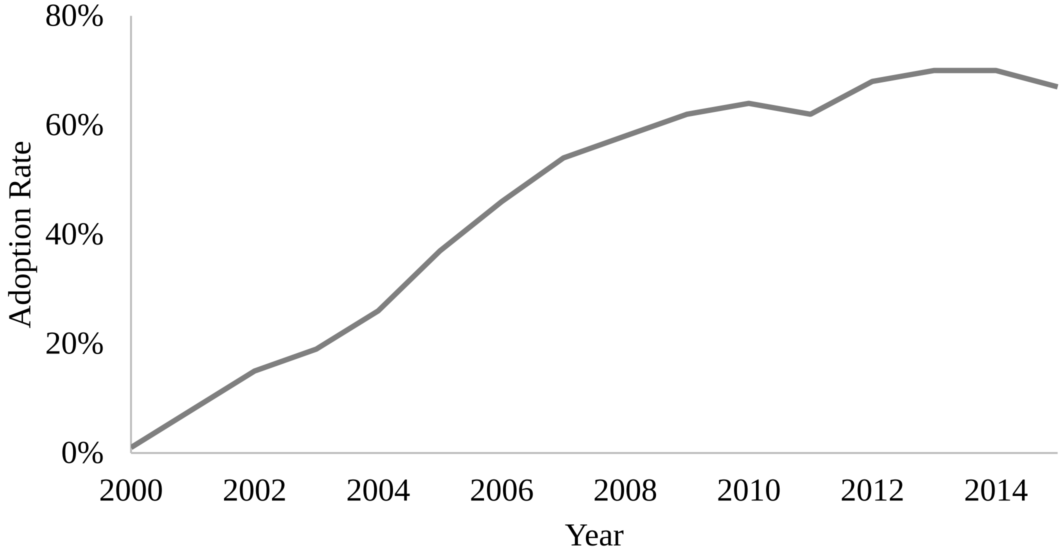
This study examines the effectiveness of Connected Nation's broadband adoption-oriented programs using generalized difference-in-difference methodology. The method is estimated under two assumptions: 1) state-level selection and 2) county level selection to the program. By exploiting both within-group (state and county) as well as time variation in the longitudinal data set, the effect of the program on broadband adoption rates can be estimated. Although the average effect of the program is found to be insignificant, there is evidence of a possible linear effect.

The results of Tables 2.2 and 2.3 provide similar results with models 1 through 3 indicating an insignificant effect of the program. In models 4 and 5 of both tables, the initial effect is negative followed by a positive trend. The results of the two models vary slightly due to the amount of group-level variation. The positive, significant linear trend in both specifications could be due to the model capturing the trend of treated counties maintaining normal growth while all other counties experienced a decrease in adoption in 2016 (Figure 2.3). This could indicate that while the Connected Nation program did not have an initial positive impact, the value of a connection was established and those in treated counties chose to continue their connection whereas others did not. Because the county-level estimates captured a larger portion of the variation in adoption rates, final conclusions of the effect of the program are drawn from these models (Table 2.3). These results reveal that the program had no significant initial impact on increasing broadband adoption rates in the year it was enacted, but did indicate a significant linear trend associated with the program.

This analysis of the Connected Nation program is primarily limited in two ways: 1) the measurement of the data and 2) the local nature of the effect of the program. The data provided by the FCC Form 477 measures broadband adoption in 5 categories covering 20% increments in adoption. To capture a significant change in adoption due to the Connected Nation program, the county and program in question would have had to increase enough to move to the next highest 20% category. As such, the program could have had a positive impact, but due to the nature of the data it was not revealed in the analysis. This draws into question the reliability of county-level data for analyses of this type. While the ACS plans to improve the quality of broadband data collected, the new survey results are not be available until September 2017 (Census, 2017). Secondly, because the program works at the county-level with individuals, capturing small individual changes can be difficult to measure with aggregate measures.

It is important to understand the potential impact of demand-side broadband adoption-oriented programs. When evaluating policies, it is crucial for government policy to understand the effectiveness of the programs that receive funding so that funds can be used in the most effective way to increase adoption. Inasmuch as adopting (and using) broadband is a focus of digital divide policy, our options must consider the means to encourage people to subscribe to broadband services once they are present.

Figure 2.1. Home Broadband Use



Source: Pew Internet Surveys, Home Broadband Use, 2000-2015

Figure 2.2. Connected Nation Particpants and Change in Adoption Rate 2 Years After Program

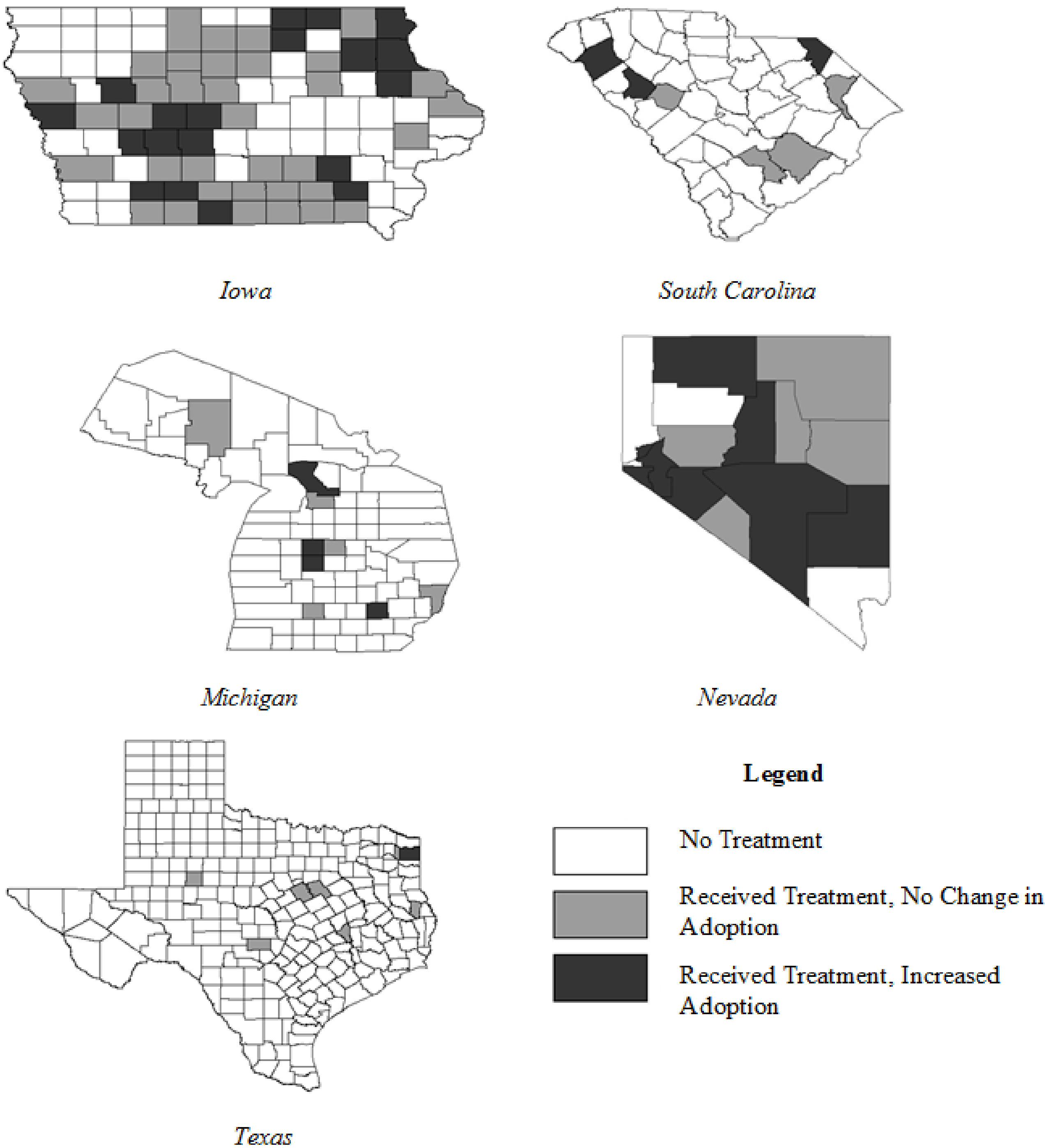
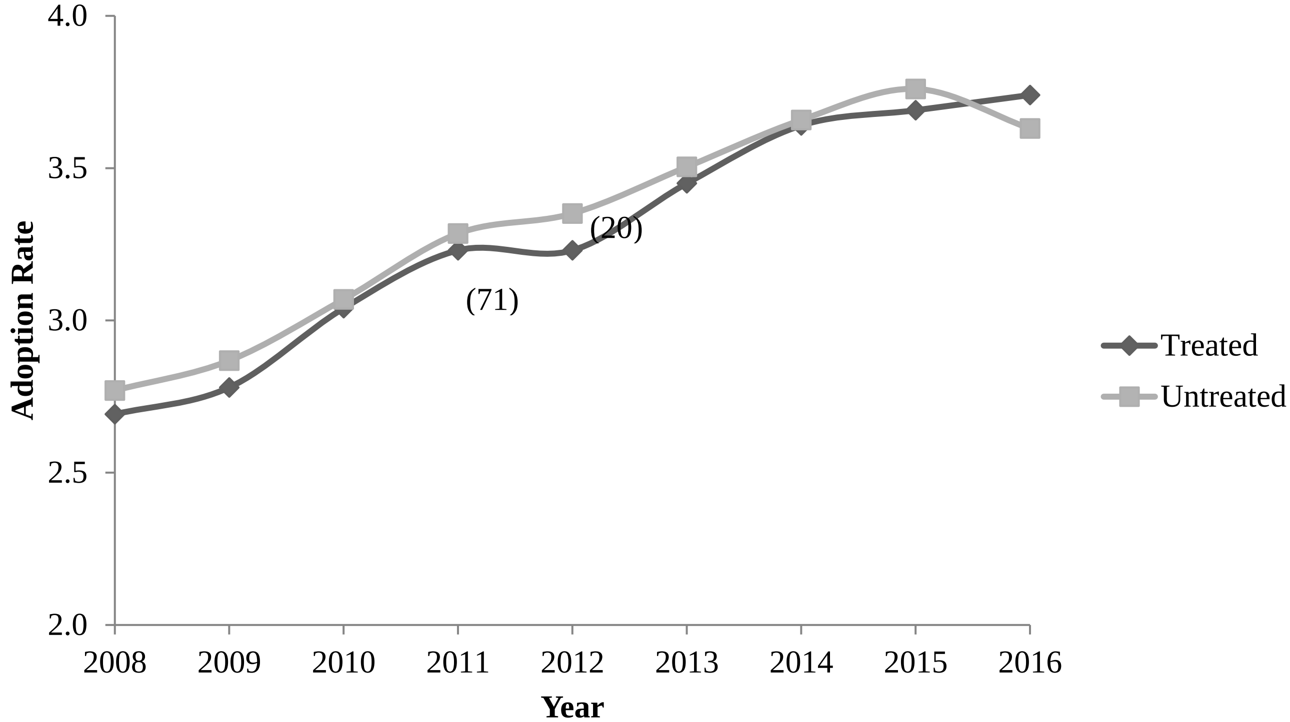


Figure 2.3. Broadband Adoption Rates



Source: FCC Form 477 (2008-2016); *Note:* (Adoption Rate) 1: 0-19.9% adoption, 2: 20-39.9% adoption, 3: 40-59.9% adoption, 4: 60-79.9% adoption, 5: 80-100% adoption; (##) number of counties entering the treatment group

Table 2.1. Mean Demographic Characteristics by Treatment Group

	Counties Included		Population		Per Capita Income		Poverty (%)		Unemployment (%)	
Year	Treated	Untreated	Treated	Untreated	Treated	Untreated	Treated	Untreated	Treated	Untreated
2008	-	2,899	-	97,599	-	33,894	-	15.24%	-	5.7%
2009	-	2,899	-	98,480	-	32,907	-	16.29%	-	8.9%
2010	-	2,899	-	99,328	-	34,002	-	16.72%	-	9.2%
2011	-	2,899	-	100,095	-	36,620	-	17.21%	-	8.6%
2012	71	2,828	31,060	102,618	40,116	37,896	14.0%	17.25%	6.4%	7.8%
2013	91	2,808	35,284	103,743	39,946	38,760	14.5%	17.29%	6.4%	7.3%
2014	91	2,808	35,496	104,544	40,743	39,927	14.2%	16.89%	5.5%	6.2%
2015	91	2,808	35,734	105,338	41,902	40,734	13.7%	16.34%	4.9%	5.5%
2016	91	2,808	35,957	106,097	41,855	40,924	13.4%	15.97%	4.5%	5.3%

Source: BEA Personal Income, Population, Per Capita Income (2008-2016); Census Small Area Income and Poverty Estimates (2008-2016); BLS Local Area Unemployment Statistics (2008-2016)

Table 2.2. Effects of Connected Nation Program on Broadband Adoption (State-Fixed Effects)

Statistic	1	2	3	4	5
Program effect	-0.010	-0.077	-0.020	-0.166	-0.109
SE	0.043	0.048	0.023	0.021	0.032
p	0.825	0.110	0.385	0.000	0.002
Yearly program effect	-	-	-	0.047	0.047
SE				0.025	0.019
p				0.071	0.021
Covariates	No	No	Yes	No	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.124	0.276	0.484	0.276	0.484

Note: For model 2-5 standard errors are calculated using a Huber-White robust variance matrix that allows for clustering at the state-level.

Table 2.3. Effects of Connected Nation Program on Broadband Adoption (County-Fixed Effects)

Statistic	1	2	3	4	5
Program effect	-0.010	0.044	0.033	-0.034	-0.043
SE	0.043	0.037	0.037	0.039	0.040
p	0.825	0.245	0.364	0.385	0.282
Yearly program effect	-	-	-	0.041	0.040
SE				0.018	0.017
p				0.020	0.018
Covariates	No	No	Yes	No	Yes
County Fixed Effects	No	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.124	0.645	0.653	0.645	0.653

Note: For model 2-5 standard errors are calculated using a Huber-White robust variance matrix that allows for clustering at the county-level.

CHAPTER III

ASSESSING THE NEED FOR A MEASURE OF BROADBAND ADOPTION INEQUALITY

Abstract

Broadband adoption is primarily measured as the percentage of a population with a connection, regardless of the modality used (i.e. fixed, mobile, or both). This results in a binary measurement that distinguishes between two groups: the percentage that have the defined level of access and those that do not. However, this measure fails to capture differences that may exists in how users connect – for example, those who use both mobile and fixed versus those use mobile only. This article proposes the use of the absolute value index (AVI) as a measure to study broadband adoption inequality. Using nationally representative data, adoption is broken into four types of connections (none, mobile, fixed, both) to compile the AVI. This measure of inequality may better represent the disparities associated with broadband use across the country, particularly as mobile internet use rises. The results indicate that the AVI can be useful in differentiating adoption patterns (i.e. mobile vs. fixed) in states with similar aggregate levels of adoption. Two nonnested hypothesis tests formally explore the explanatory power of the two measures in explaining economic relationships commonly associated with broadband adoption, and conclude that the AVI does not capture any additional information.

Keywords: Absolute Value Index, Inequality, Broadband Adoption

Introduction

Broadband adoption[9] is primarily measured as a percentage of the population that has a connection, regardless of the modality used (a fixed (wired) or mobile (wireless) plan). These measures are often broken down across groupings of speeds and demographics to provide a more detailed picture of the state of adoption (FCC, 2016). This measurement system produces a binary measurement resulting in two groups: the percentage that have the defined level of access and those that do not. For example, Pew Internet report the percentage of rural residents who adopt (63%) versus a corresponding number (73%) in urban areas (Perrin, 2017). While this measure gives a broad overview of who is using broadband, it lacks in providing insight into the *inequality* associated with broadband adoption – in particular, whether the user has a fixed or mobile connection (or both). This paper uses the absolute value index to compose a measure of broadband adoption inequality and then assesses its effectiveness compared to the traditional measure (percent of adopters) typically used.

Measuring inequality allows for the policy decisions surrounding broadband adoption rates to be viewed as a social welfare question, which furthers the primary descriptive measures typically used (Kaplow, 2002). In order to make the claim that broadband adoption is in fact a question of social welfare, one must first make the assertion that broadband has positive effects for its users. A large number of previous papers have built the case that broadband positively affects issues ranging from education to civic engagement, which are covered in the literature review. The measurement of

[9] In 2015, the Federal Communications Commission (FCC) defined broadband as a connection with a minimum 25 Mbps download speed/ 3 Mbps upload speed (FCC, 2015)

broadband inequality must start by making assumptions on the ordinal level of utility associated with each connection type (Figure 3.1). For the purpose of this paper the levels of adoption, in order of increasing utility, will be defined as households with no connection, a mobile-only connection, a fixed, home connection, and those with both (None < Mobile-only < Fixed-only < Both)[10]. Thus, those with both types of connections are assumed to have a higher utility than those who use just one. Additionally (and perhaps controversially), fixed connections are assumed to have higher utility than mobile. Those with a mobile-only connection are defined as adopters who access the internet via a mobile data network only, while fixed adopters are those with a traditional (DSL, Fiber, Cable, Etc.) wireline connection in the home. The mobile-only connection has been hypothesized to be inferior to the fixed, home connection for many reasons. In a survey by the Pew Research Group, it was reported that 30% of mobile-only users reached their data caps, therefore limiting their access (Smith, 2015). It was also reported that mobile-only users had issues with non-mobile optimized content, small screen size, and difficulty typing on their mobile devices (Anderson & Horrigan, 2016). Reisdorf et al. (2018) also hypothesize difficulty with reading content on mobile devices. Considering the limiting factors of a mobile-only connection, this paper assumes that the utility from a fixed, home connection is greater than that of a mobile-only[11]. The rankings of ordinal utility used in this paper are consistent with the FCC's Progress Report (2016) in which they suggest that there exists an inherent difference in the capabilities of a

[10] Alternative models, in which mobile-only and fixed-only were merged to create three levels of ordinal utility (no connection, with mobile or fixed, and both) resulted in similar findings.
[11] However, The FCC notes that consumers who are forced to choose between their services for economic reasons generally prefer mobile (FCC, 2018).

mobile and fixed connection, and that to maximize the telecommunications capability of individuals and households; they should be adopters of both. (FCC, 2016).

The paper proceeds as follows: first, a brief review of the literature is given, the data and methodology are introduced, and the paper is concluded by comparing the absolute value measure of adoption inequality to the traditional percentage based approach using two nonnested hypothesis tests.

A Brief Review of the Literature

Measuring Inequality

While the study of inequality was originally introduced by statistician and sociologist Corrado Gini to study income, it has since been expanded to many other fields (Santos and Guerrero 2010). Most notably, the health field has published extensively on the inequality of individual health status. The Center for Disease Control and Prevention (CDC) measures inequality for a variety of health reported data and uses these measures to make comparisons and policy recommendations across states (CDC, 2011). Marmot (2005) studied the inequality of life expectancy across countries using socioeconomic factors to explain the differences. The inequality of educational achievement and educational opportunity have also been studied using similar techniques (Ferreira & Gignoux, 2011). Studying all aspects of inequality is important as increases in social and economic inequality play an important role in developing social hierarchy, status, and class (Wilkinson & Pickett, 2010). For the case of broadband, it is also important to study inequality and its use as tool for assessing programs aimed at increasing adoption. For example, in evaluating an adoption-oriented program – the program could have increased overall utility associated with broadband by encouraging households to switch from a fixed-only connection to both. This change would be reflected in the inequality of adoption, but the overall adoption rate would remain the same.

While the largest part of current broadband literature measures adoption as the percentage of households with a connection, some research has focused of the topic of inequality. Gallardo (2017) introduced the Digital Divide Index (DDI) as a measure of broadband inequality at the county-level. The DDI is composed of weighted information on two areas of interest: 1) the current state of broadband infrastructure including: the percent of the population with no access to a fixed connection, average upload/download speeds, and the number of fixed, residential connections and 2) socioeconomic characteristics including: percentage of the population over 65, those over 25 with less than a high school degree, and individual poverty rate. This results in a DDI score ranging from 0% to 100%. Counties with higher scores are lacking in broadband infrastructure and simultaneously at greater risk of lagging in the adoption of new technology. Note, however, that the access measure used for broadband is still binary in nature. Hargittai (2002) examined the inequality of internet related skills among users and found that the largest inequalities in skills existed among differences in age, education, and prior experience with technology. Other studies also support these findings, asserting that a new digital divide exists among users relating to their skill sets – including those associated with smartphone use (Lee et al., 2014; Warchauer & Dowding, 2004).

Economic Impacts of Broadband Adoption

A large number of previous studies have linked increases in broadband access and adoption to increases in economic and civic well-being within communities and households. The diffusion of broadband has been cited to have impacts on economic health, healthcare, education, and social engagement, and is very well documented in the literature. One of the mostly widely cited works on broadband impact, Lehr, Osorio, Gillet, and Sirbu (2006), established that in comparison to communities without broadband during the period of 1998 to 2002, those with broadband experienced larger growth in the areas of employment, businesses, and increases in IT-related business sectors. Koutroumpis (2009), found that increases within a country's broadband infrastructure lead to overall GDP growth for that country. Focusing on a more local impact, Kolko (2012) found that an increased number of broadband providers in a community lead to employment growth in all industry codes defined by the North American Industrial Classification System (NAICS). An analysis of the United States Department of Agriculture's low-cost broadband loan programs found that increases in infrastructure lead to positive impacts on farm sales and profit in a set or rural counties (Kandilov et al., 2017). Kim and Orazem (2017) reported a significant relationship between broadband availability and the location decision of new firms in rural areas.

Others argue that it is the adoption of broadband internet rather than the infrastructure that is more closely associated with economic improvements. A study in 2014 found that rural areas with high broadband adoption rates experienced larger growth in median household income, total employment, and an increase in the number of firms in comparison to those areas without (Whitacre, Gallardo and Strover, 2014). Areas with higher broadband adoption rates are also associated with higher levels of civic engagement, increased voter turnout, greater willingness to contact a government official, and increases in interacting with neighbors (Whitacre and Manlove, 2016). Several studies have found that providing technology to households with children can reduce school performance proficiency gaps and increase cognitive ability (Shapley et al., 2007; Malamud & Pop-Eleches 2010)[12]. The impact of broadband adoption in rural areas has also been a topic of research interest. Stenberg et al. (2009) suggested that rural communities can benefit from increases in broadband adoption, particularly in the areas of distance education, telehealth, and telework.

While the majority of these studies have focused on the impact of a fixed broadand connection, less attention has been paid to the impacts of a mobile connection. Prieger (2013, 2015) finds that the potential impact of a mobile connection is becoming increasingly important as it has the potential to allow minorities and those in rural areas to experience the positive impacts of adopting a connection. Studying the impact of a mobile connection is also important as the percentage of households adopting through a mobile-only connection more than doubled from 2011 to 2015. Manlove and Whitacre (2018) assert that this trend to mobile is primarily driven by increased mobile speeds associated with the roll out of Long-term evolution (LTE) coverage. In general, all of these studies have used the mean values of adoption or infrastructure availability to study the effects of broadband. This paper seeks to extend this research by assessing the need for a measure of inequality in further exploring the relationship of broadband and economic and social growth.

Data

To examine the distribution of broadband adoption inequality, Current Population Survey (CPS) data is used. The CPS is a monthly survey by the U.S. Census Bureau that collects

[12] Note that other studies on broadband access and scholastic achievement are less enthusiastic (Vigdor et al., 2014).

information from individuals and households pertaining to employment status, earnings, and education. The CPS interviews approximately 50,000 households monthly, and is a nationally representative data set when survey weights taking into account current estimates of the demographic composition are applied. In addition to the monthly surveys, supplemental surveys are used to gain information for more specialized information. The CPS administers the Computer and Internet use supplemental file in conjunction with the National Telecommunications and Information Administration to gain "information about household access to computers and use of internet." The CPS supplemental surveys for July 2011, 2013, and 2015 are used for this analysis (Census, 2011, 2013, 2015)

The supplemental survey on computer and internet use asks each household how their home connects to the internet. Starting in July 2011, households were presented with the following question about their connection type (shown below). This allows households to be categorized into the four following categories: 1) households with no internet connection, 2) households with a mobile-only connection, 3) households with only a fixed, home connection, and 4) households with both a mobile and fixed connection[13]. Note the increase in mobile-only and both over time, while wired-only access declines notably (See Figure 3.2). The data captured in this question provides purely ordinal results, as the CPS has no defined download/upload thresholds for their definition of adoption. These four categories are the focus of broadband adoption inequality in this paper.

[13] For the purposes of this study, a household is defined as mobile-only if their only means of connecting to the Internet is through a paid mobile broadband plan. This plan may be used with any device such as a computer, tablet, cell phone, or smartphone. Whereas a household is considered fixed-only if their only means of connecting is through a fixed, in home plan.

CPS Connection Type (July 2011, 2013, 2015)

At home, does anyone in this household access the internet using…

(Select all that apply)

(1) Dial-up service?

(2) DSL service?

(3) Cable modem service?

(4) Fiber-optic service?

(5) Mobile broadband plan?

(6) Satellite service?

(7) Some other service?

Combining this data on connection type with demographic variables from the survey allows for studying which socio-demographic groups have the highest levels of adoption inequality. Demographic information is available for each household that answered the CPS. Summary statistics by adoption level are shown in Table 3.1. Generally, income levels increase as the level of adoption increases, with households that have no connection largely earning less than $30,000. Households with an education level of some college or higher are more likely to have a connection (of any type) in comparison to those with a high school education only. Age generally declines with the level of connection, with the mean age decreasing as the connection level rises. Households with higher numbers of children in the home are much more likely to have both a fixed and mobile connection in comparison to those households without, while adopters in non-metro areas are less likely to have a higher level of adoption than those in metro areas. Employment status has a positive relationship with level of connection: as the likelihood of being employed increases, so does the probability of having a higher level of adoption. In addition, the adoption data is also meshed with four economic indicators commonly cited to be impacted by broadband. The summary statistics of these variables are presented in Table 3.2. Generally, overtime the economic indicators all indicate improvement, as income and the percentage of those with a bachelors degree or higher increase while poverty and unemployment fall overtime.

Methods

The categories of broadband adoption level used here are purely ordinal rankings, which have the distinct feature that the order is the only relevant information. Therefore, when developing an index of adoption inequality it is important that the index be invariant to the rescaling of the variables. It is well documented that traditional measures of inequality such as the Gini coefficient, Atkinson Index, and Theil Index do not have this property, as their formulas are dependent on the mean of the distribution (Zheng, 2010; Allison & Foster, 2004). As such, many indices for ordinal data have been introduced, including those by Blair and Lacy (2000), Allison and Foster (2004), Abul Naga and Yalcin (2008), and Zheng (2010). The index proposed by Abul Naga and Yalcin (2008) allows for weights to be placed on either end up the distribution to account for aversion towards lower levels of connection, and is thus used for this paper.

The Absolute Value Index

The absolute value index (AVI) uses the cumulative distribution of the ordinal ranking data to measure inequality by taking into account the number of people in the distribution that are above or below the median level of adoption. A fixed-only connection is the median for all states used in our sample. The level of aversion to inequality above or below the median may be altered based on preferences about the distribution. Two parameters (α, β) are introduced into the model to control for this preference: when $\alpha > \beta$ the index is more sensitive to inequality *below* the median and more sensitive to inequality *above* the median when $\beta > \alpha$. The index can thus be expressed as

(1) $$I_{\alpha,\beta} = \left(\frac{\sum_{i<m} P_i^{\alpha} - \sum_{i\geq m} P_i^{\beta} + (n+1-m)}{k_{\alpha,\beta} + (n+1-m)}\right), \quad \alpha, \beta \geq 1$$

$$k_{\alpha,\beta} = (m-1)\left(\frac{1}{2}\right)^{\alpha} - \left[1 + (n-m)\left(\frac{1}{2}\right)^{\beta}\right]$$

where $I_{\alpha,\beta}$ is the absolute value index for the given measures inequality aversion parameters of α and β, m is the median state of the distribution (fixed-only), n is the number of ordinal levels, and P_i is the probability of the level i occurring. The index is calculated at $\alpha, \beta = \{(2,1), (3,1), (4,1)\}$ to demonstrate increasing aversion to inequality below the median- or, in the case of broadband adoption more aversion to those with a mobile-only connection or less. This method of increasing aversion parameters around the distribution of interest (below the median) follows the work of Naga and Stapenhurst (2015) and Jorda et al. (2013). The resulting AVI represents the observed level of inequality in each case where the higher the AVI the greater the level of inequality observed. The absolute value index is calculated for each state in the United States to allow for comparison of the observed level of adoption inequality in each.

Assessing the Quality of the AVI compared to Percent Adoption

To assess the need for a measure of inequality in addition to the traditional percentage based approach typically used, four measures of economic well-being commonly cited to be impacted by broadband adoption (median household income, poverty, unemployment, and gross state product) are regressed against both the AVI and percent adoption to assess their ability to explain these measures using two non-nested hypothesis tests (Whitacre, Gallardo, & Strover, 2014; Koutroumpis, 2009; Minges, 2016; Thompson & Garbacz, 2011). The use of nonnested hypothesis tests has been used extensively in the literature to explore the explanatory power of models (Ghali, 2007). The variables all display highly significant measures of spatial autocorrelation, as measure by the Moran's I value[14]. All Moran's I values were significant at the *p=0.05* level. As such, a spatial econometric approach is used to model the two competing models to determine if percent adoption or the AVI serve as a better indicator for the variables chosen. To test for the appropriate spatial model, a Lagrange multiplier (LM) tests is used (Anselin et al., 1996). The results of the spatial dependency analysis, after running the standard OLS showed that, for each variable the LM statistic for spatial error was greater than that of the spatial lag model, thus providing evidence that the spatial error specification is the correct choice. The formal competing spatial error models are:

(2) $$H_0: y_1 = \propto + \beta_{AVI} AVI_i + \mu_i$$

$$\mu_i = \lambda W \mu_i + e_i$$

and

(3) $$H_1: y_2 = \propto + \beta_{Percent} Percent_i + \mu_i$$

$$\mu_i = \lambda W \mu_i + e_i$$

where y_i is one of the four economic indicators commonly cited to be impacted by broadband adoption, $\propto$ is the intercept, AVI and $Percent$ are the two nonnested, competing variables, W is a spatial weight matrix (a queen contiguity matrix is used in practice), and e_i is the associated zero-mean error term. The two tests for comparing these hypotheses (model H_0 vs. model H_i) are discussed below.

[14] Moran's I is a measure of spatial autocorrelation, ranging from -1 to 1 where 0 represents a purely random spatial distribution and 1 represents a complete spatial autocorrelation (where a state's value is dependent entirely on its neighbors).

Encompassing Test

The encompassing test is performed by formulating a model which *encompasses* the explanatory variables of both models into one equation such that

(4)
$$y_i = \propto + \beta_{AVI} AVI_i + \beta_{Percent} Percent_i + u_i$$
$$\mu_i = \lambda W \mu_i + e_i.$$

The first specification is rejected, with broadband measured by the AVI, if $\beta_{AVI} = 0$ by a conventional F-test, this would indicate that percent adoption is the preferred variable and is more strongly associated with the outcome variable. The second specification is rejected, percentage adoption, if it is found that $\beta_{Percent} = 0$ by conventional F-test, similarly indicating that AVI is the preferred variable (Greene, 2000; Davidson & McKinnon, 1982). The full interpretation matrix for the results of the F-tests are presented in Table 3.2.

J-Test

The J-Test for testing hypotheses in nonnested models is adapted from Davidson and MacKinnon (1981, 1993). This approach is performed by first considering a compound model such

(5)
$$y_i = (1 - \theta) X\beta + \theta Z\gamma + u_i$$
$$\mu_i = \lambda W \mu_i + e_i$$

where X denotes the set of explanatory variables in equation 2 (AVI) and Z denotes the set of explanatory variables in equation 3 (Percent Adoption). When $\theta = 0$ the model collapses to Equation 2, and when $\theta = 1$ the model collapses to equation 3. Because the parameters of the compound model are not identifiable (θ), Davison and MacKinnon suggest replacing the compound model (5) and estimating one such that "the unknown parameters of the model *not* being tested are replaced by estimates of those parameters" (Davidson & McKinnon, 1991, pg. 382). To test equation (2) γ is replaced by its estimate $\hat{\gamma}$ which is obtained from regressing y_i on Z, writing the results as $\hat{y}_2 = Z\hat{\gamma}$ the following is tested:

(6) $$y_i = (1-\theta)X\beta + \theta\hat{y}_2 + \varepsilon.$$

Similarly, to test equation (3) the following model is estimated under the same conditions:

(7) $$y_i = (1-\theta)\hat{y}_3 + \theta Z\gamma + \varepsilon.$$

The results of the J-Tests are interpreted by examining the significance of the added regressor $\hat{y}_i$. If the added regressor is significantly different from zero in equation (6), AVI is rejected in explaining y, if the added regressor in equation (7) is significantly different from zero, Percent Adoption is rejected in explaining *y* (Ghali, 2007).

Results

State-Level Absolute Value Index

The state-level measures of the absolute value index allow for comparing and ranking states by their level of adoption inequality. Figure 3.3 presents the 2015 index for each state with aversion parameters (α,β)=(4,1) (representing the highest level of aversion to inequality below the median) as well as the traditional percentage adoption measure for comparison. Higher levels of inequality are generally concentrated in the southern region of the United States. The same is generally true for adoption measured as a percentage; however clear differences can be seen in the lowest quartiles. Both the AVI and percent adoption demonstrate positive, significant Moran's I measures of spatial autocorrelation, 0.48 and 0.30 respectively. This indicates that states with high levels of inequality are likely to be surrounded by states with similar inequality, and the same is true (but to a lesser degree) that states with higher adoption are surrounded by other states with high adoption. This relationship between states with similar AVI and percent adoption can be visualized (Figure 3.4) using LISA cluster maps[15]. The LISA maps indicate that for 2015 AVI, eight states have a high-high relationship, indicative that those states are significantly surrounding by other states with high inequality. Conversely, for percent adoption the LISA maps indicate that seven states have significant low-low relationships (states with low levels of adoption are surrounding by other states that are also low adopters).

A bivariate Moran's I can be used to understand the correlation of AVI to the spatial lag of percent adoption. These results will indicate if states with high inequality are surrounded by states with high or low levels of percent adoption. The global bivariate Moran's I between the two variables reveal a significant, negative relationship (-0.38); meaning that as the spatial lag of percent adoption decreases the AVI measure increases for surrounding states. A bivariate Lisa cluster map, similar to the method above can be used to visualize this relationship (Figure 3.5). These results indicate seven of the states have a significant low-high relationship between percent adoption and AVI. When ranking the states by level of observed inequality, all five of the states with the highest level of inequality are located in the South (Table 3.4). Comparing the rankings of the AVI to percent adoption reveals that of the five states with the highest level of inequality, two of those states are also among the top five lowest adopting states when measured as a percentage. Similarly, five of the states with the lowest level of inequality are also those

[15] Local Indicator of Spatial Association (LISA) Cluster Maps give an indication of significant clustering of similar observations around a single observation.

among the top three adopters measured as a percentage. The full results for each year and level of aversion are available for each state in Appendix 3A.

Results of Tests Assessing the Quality of the AVI compared to Percent Adoption

Using the Encompassing and J-Tests allows for formally comparing the two variables performance as an explanatory variable. The results of the Encompassing test are presented in Table 3.5. Of the twelve scenarios examined (four variables across three years), six indicate that AVI and percent adoption contain the same information (50%), four favor measuring broadband as the percentage of adopters (33%), and two favor the AVI (17%) at the 0.05 significance level. These results indicate that the new measure, AVI, performs in a way similar to the traditional measure. The results of the J-Test reveal similar findings; six of the results are inconclusive finding no difference between the two measures, four favor percent adoption as the optimal model, and two favor the AVI.

Conclusions

This article proposes the use of the Absolute Value Index as a measure of inequality in broadband adoption and formally tests the need for such a measure using two nonnested hypothesis tests. The results of the state-level measures of inequality demonstrate that the AVI performs in ways similar to measuring adoption as a percentage. While the AVI is not dramatically different, it does provide a way to differentiate between states that have similar aggregate adoption rates. For example, Arkansas and North Carolina have similar adoption rates in 2015 (70.5% and 70.2%, respectively), but AVI measures of 2.51 and 2.39, respectively which is a result of Arkansas having higher mobile-only adoption rates than North Carolina. The same technique can also be applied to states with similar high levels adoption such as Idaho and Wisconsin, which both have aggregate adoption rates 81.9%, but AVI measures of 2.29 and 2.13, respectively. Being able to distinguish between states that may have similar adoption percentages will prove useful for targeting specific states for government funding aimed at increasing adoption. While the AVI does have some potential value in ranking states, the results of the nonnested hypothesis tests indicate that it may provide no additional information when used as an independent variable in explaining economic relationships associated with broadband. The results of the regressions are limited in that they are simple bivariate regressions, which may suffer from omitted variable bias. However, we believe that this analysis is an important step in contributing to the study of inequality in broadband adoption.

Figure 3.1. Level of Ordinal Utility by Adoption Level

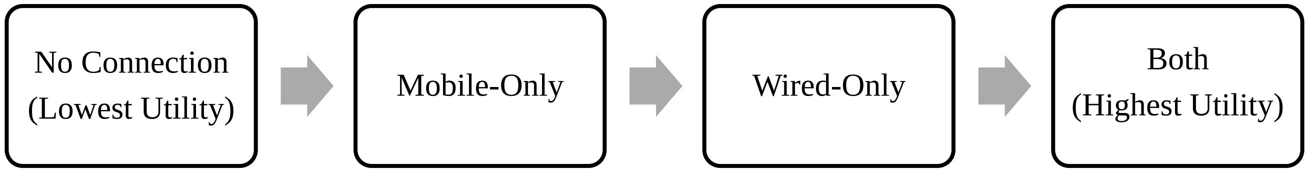
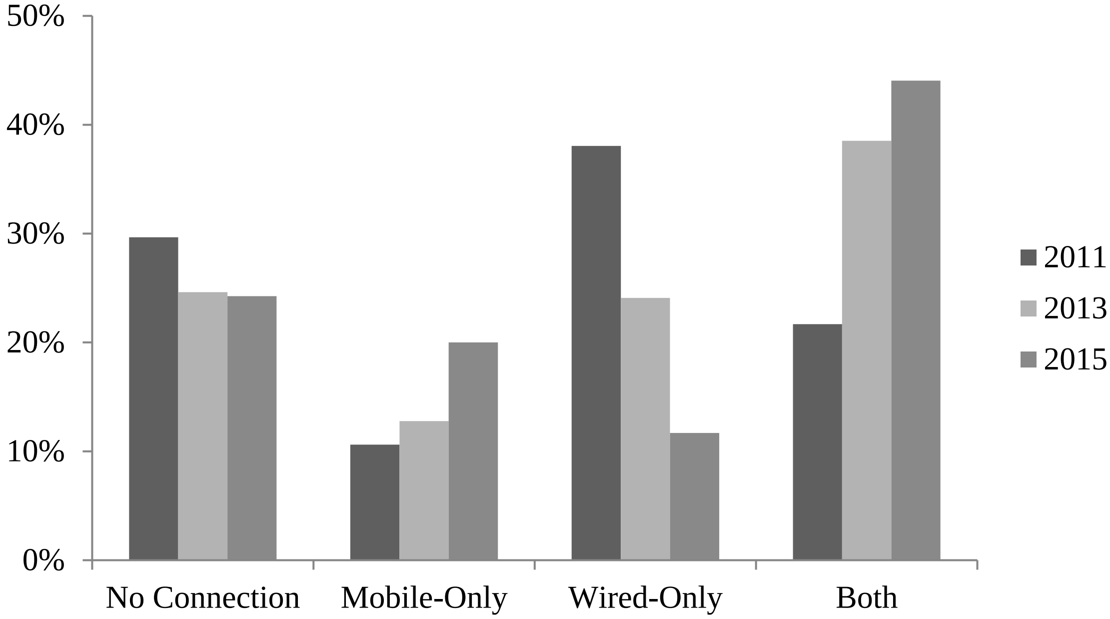
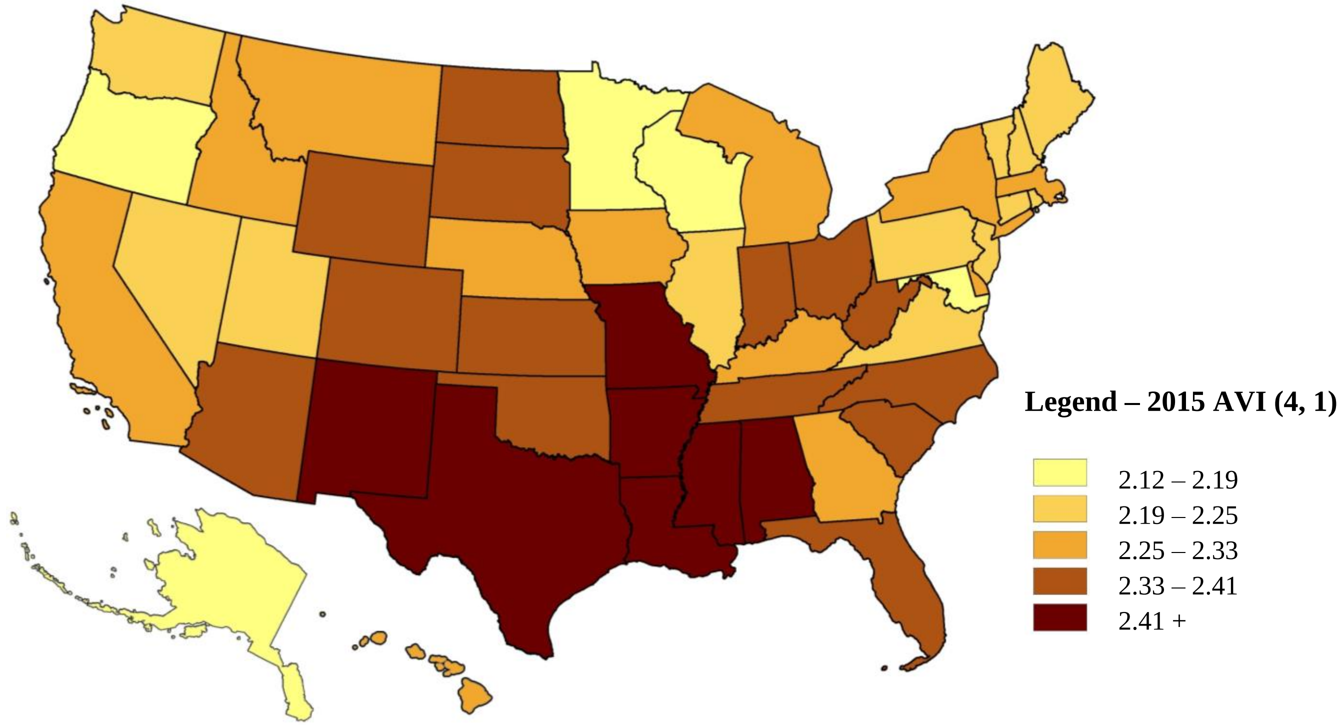


Figure 3.2. Broadband Adoption Type



Source: Current Population Survey, Computer and Internet Use Supplement (2011, 2013, 2015)

Figure 3.3. Map of 2015 Absolute Value Index and Percent Adoption



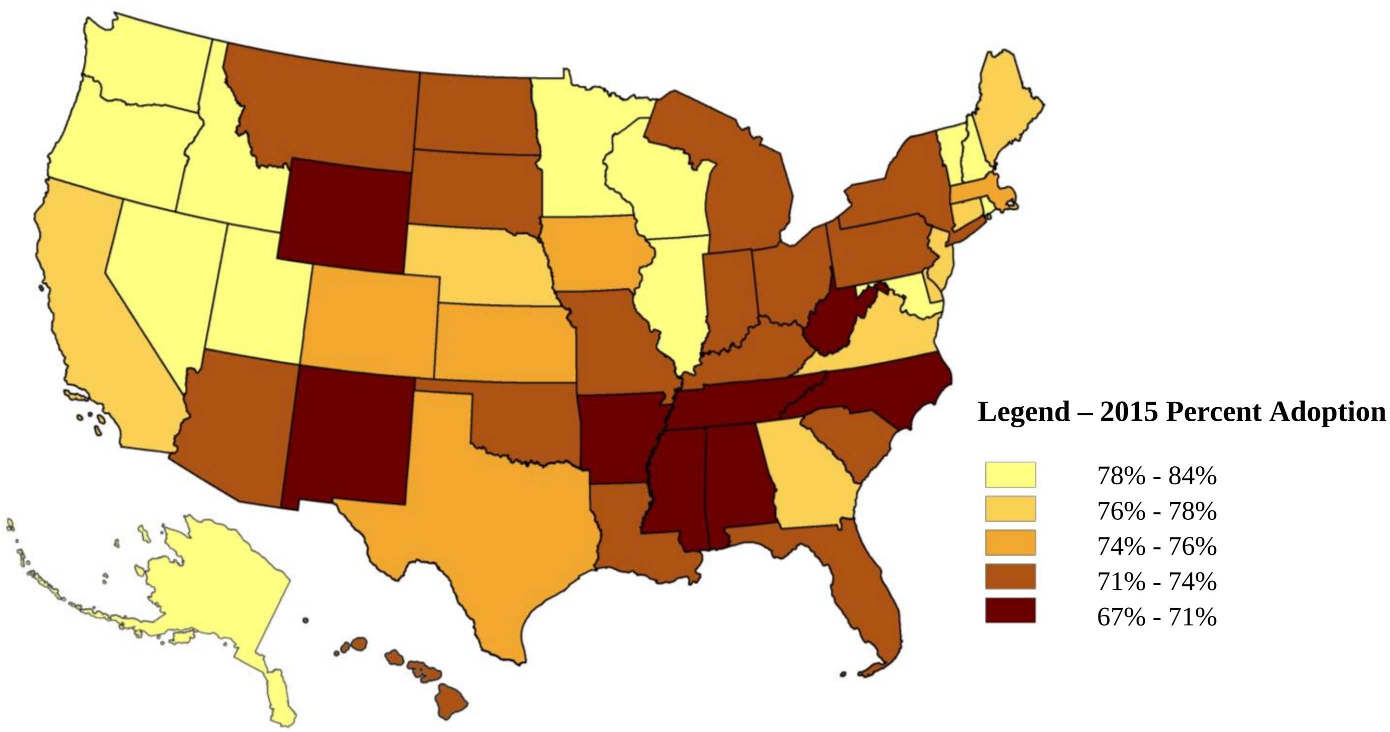
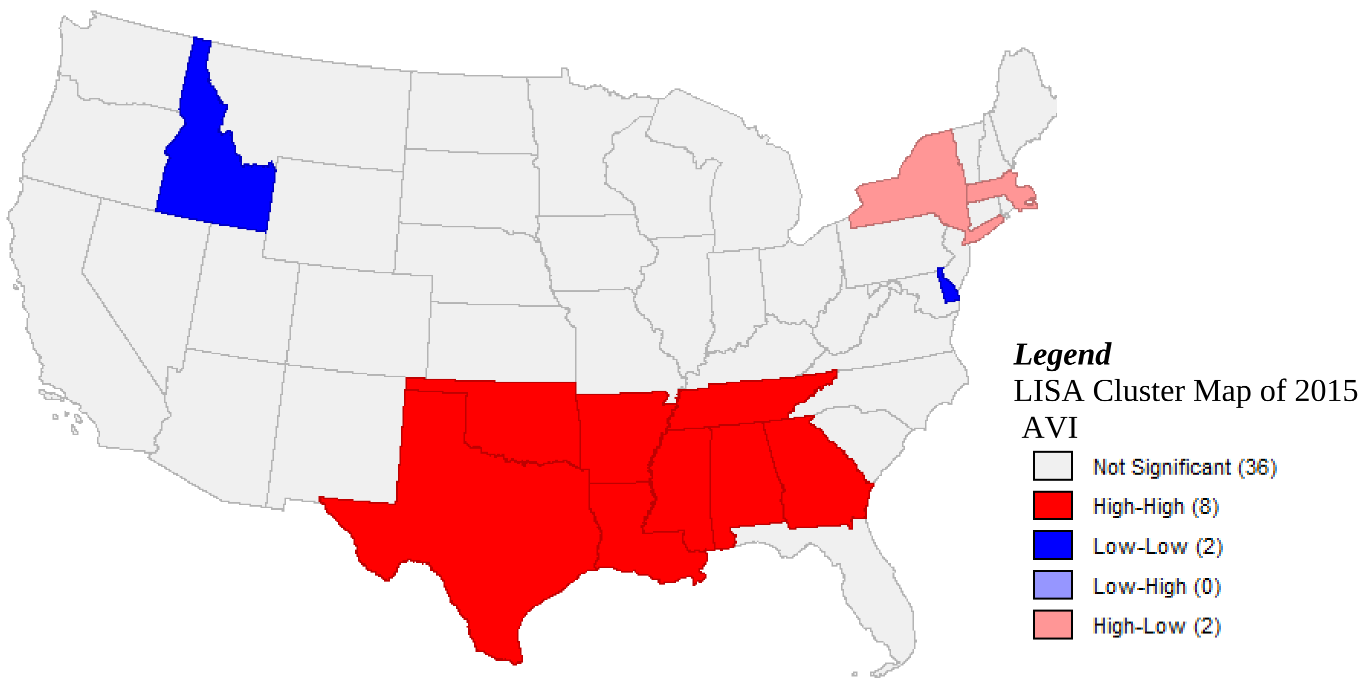


Figure 3.4. LISA Cluster Maps of AVI and Percent Adoption for 2015



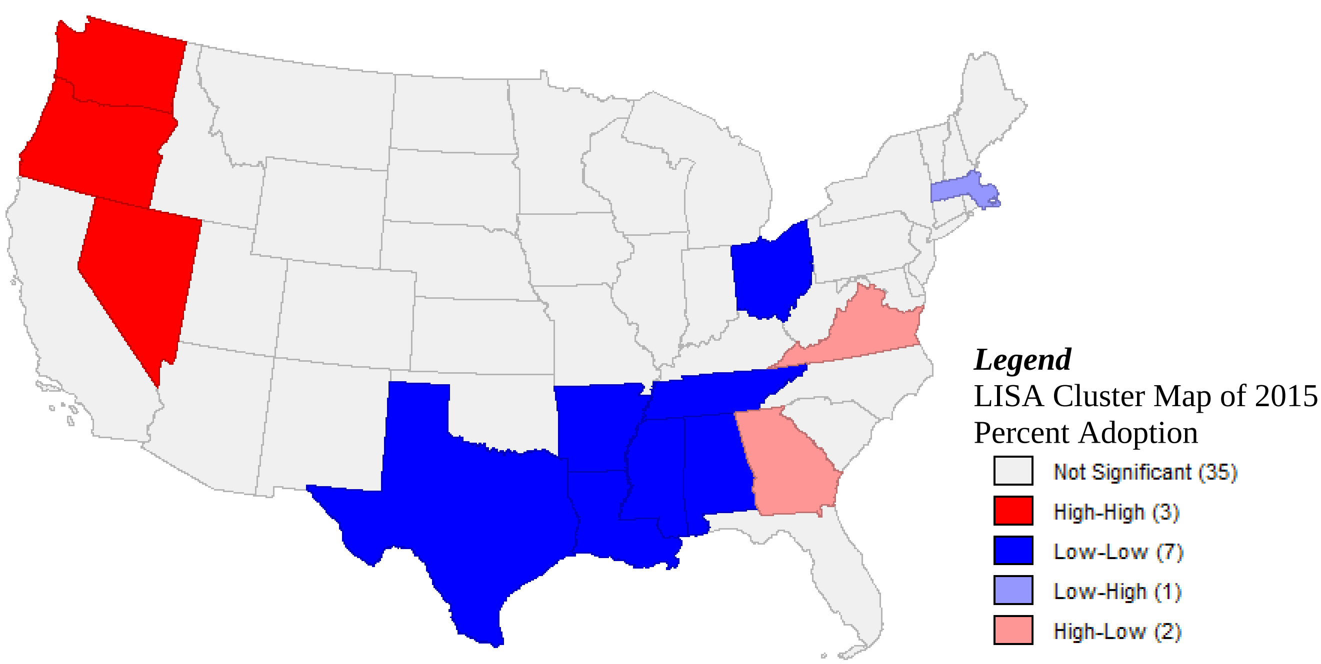


Figure 3.5. Bivariate LISA Cluster Map of AVI and Percent Adoption 2015

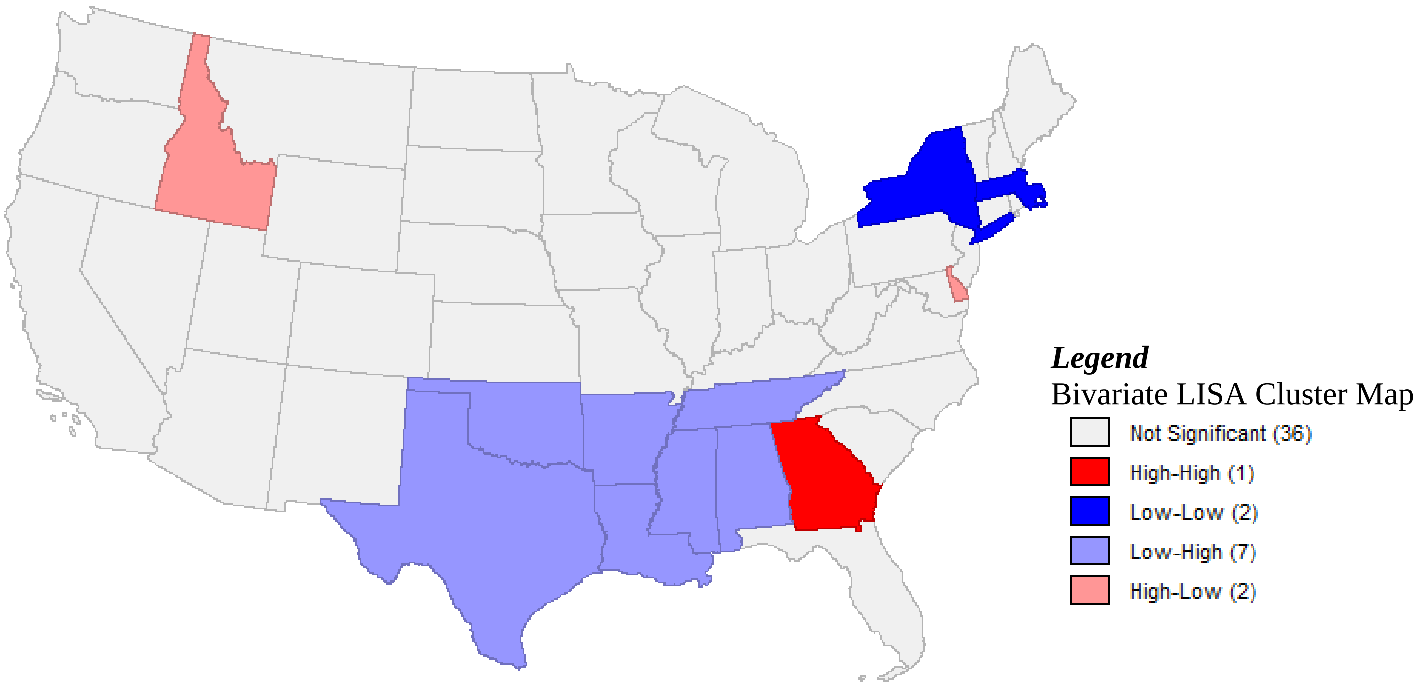


Table 3.1. CPS Household Characteristics Means by Adoption Level

	2011				2013				2015			
	None	Mobile-Only	Wired-Only	Both	None	Mobile-Only	Wired-Only	Both	None	Mobile-Only	Wired-Only	Both
Adoption Rate	29.66%	10.61%	38.06%	21.68%	24.62%	12.77%	24.09%	38.52%	24.26%	20.00%	11.69%	44.05%
Income												
Less than $30,000	0.612	0.317	0.254	0.173	0.620	0.372	0.291	0.161	0.536	0.328	0.317	0.167
$30,000 - $59,999	0.269	0.288	0.324	0.273	0.261	0.310	0.325	0.258	0.264	0.302	0.332	0.266
$60,000 - $99,999	0.083	0.201	0.245	0.272	0.083	0.185	0.230	0.280	0.117	0.204	0.215	0.272
More than $100,000	0.037	0.194	0.177	0.282	0.036	0.133	0.154	0.301	0.107	0.201	0.191	0.308
Education												
High School	0.403	0.288	0.343	0.240	0.412	0.347	0.351	0.255	0.392	0.336	0.379	0.270
Some College	0.119	0.203	0.162	0.208	0.119	0.175	0.175	0.193	0.124	0.169	0.172	0.184
Bachelor	0.061	0.152	0.143	0.238	0.060	0.120	0.149	0.215	0.082	0.136	0.134	0.200
Graduate Degree	0.021	0.073	0.060	0.094	0.022	0.044	0.066	0.080	0.035	0.053	0.066	0.084
Race												
African American	0.177	0.157	0.097	0.106	0.179	0.177	0.091	0.109	0.178	0.164	0.097	0.106
Asian	0.025	0.037	0.050	0.050	0.026	0.037	0.050	0.063	0.037	0.045	0.048	0.064
Hispanic	0.168	0.127	0.103	0.094	0.169	0.169	0.100	0.118	0.168	0.177	0.098	0.120
Non-Metro Status	0.229	0.139	0.146	0.102	0.231	0.178	0.159	0.103	0.193	0.162	0.149	0.102
Age												
18 - 34	0.232	0.541	0.324	0.540	0.197	0.515	0.255	0.483	0.218	0.426	0.217	0.444
35 - 54	0.234	0.296	0.294	0.330	0.217	0.299	0.246	0.317	0.220	0.292	0.213	0.295
55 +	0.534	0.163	0.382	0.129	0.587	0.186	0.498	0.201	0.562	0.282	0.570	0.262
Number of Children in Home	0.268	0.516	0.343	0.515	0.210	0.508	0.259	0.468	0.232	0.412	0.228	0.401
Retired	0.333	0.072	0.197	0.049	0.377	0.079	0.270	0.082	0.360	0.132	0.351	0.120
Employed	0.352	0.620	0.507	0.693	0.321	0.618	0.481	0.646	0.350	0.587	0.408	0.624

Source: Current Population Survey, Computer and Internet Use Supplement (2011,2013,2015)

Table 3.2. Summary Statistics of Economic Outcome Variables

Variable	2015	2013	2011
Median Household Income	56,022	52,884	50,654
Poverty (%)	14.17%	15.08%	15.19%
Unemployment (%)	5.89%	7.74%	9.35%
Bachelors or Higher (5)	29.81%	28.88%	27.86%

Table 3.3. Interpretation of Encompassing Test

		$H_0: \beta_{AVI} = 0$	
		Not Rejected	*Rejected*
$H_0: \beta_{Percent} = 0$	*Not Rejected*	AVI and Percent Adoption Contain Same Information	Favors AVI
	Rejected	Favors Percent Adoption	AVI and Percent Adoption Each Contain Unique Information

Table 3.4. Top 5 States in 2015 with the Highest and Lowest AVI(4,1) and Percent Adoption

Absolute Value Index					
Highest Inequality			Lowest Inequality		
1.	Mississippi	2.614	1.	Oregon	2.127
2.	Alabama	2.525	2.	Wisconsin	2.128
3.	Arkansas	2.514	3.	Maryland	2.173
4.	New Mexico	2.482	4.	Minnesota	2.185
5.	Louisiana	2.466	5.	Alaska	2.187
Percent Adoption					
Lowest Adoption			Highest Adoption		
1.	Mississippi	67.42%	1.	Alaska	83.69%
2.	Tennessee	67.69%	2.	Minnesota	82.24%
3.	Alabama	68.28%	3.	Utah	82.18%
4.	West Virginia	69.27%	4.	Wisconsin	81.93%
5.	Wyoming	69.27%	5.	Idaho	81.89%

Table 3.5. Probability Values from Encompassing Test for Nonnested Models

	2011		2013		2015	
Variable	$H_0: \beta_{Percent} = 0$	$H_0: \beta_{AVI} = 0$	$H_0: \beta_{Percent} = 0$	$H_0: \beta_{AVI} = 0$	$H_0: \beta_{Percent} = 0$	$H_0: \beta_{AVI} = 0$
Median Household Income	0.000	0.299	0.003	0.081	0.177	0.047
Poverty (%)	0.002	0.821	0.000	0.866	0.199	0.004
Unemployment (%)	0.957	0.864	0.068	0.317	0.736	0.142
Gross State Product	0.908	0.724	0.938	0.622	0.950	0.896

Note: Because the numbers in the table are *p* values, values less than 0.05 are considered significant.

Table 3.6. Probability Values from J-Test for Nonnested Models

	2011		2013		2015	
Variable	$H_0: Percent$ $H_1: AVI$	$H_0: AVI$ $H_1: Percent$	$H_0: Percent$ $H_1: AVI$	$H_0: AVI$ $H_1: Percent$	$H_0: Percent$ $H_1: AVI$	$H_0: AVI$ $H_1: Percent$
Median Household Income	0.299	0.000	0.081	0.003	0.047	0.177
Poverty (%)	0.827	0.002	0.866	0.000	0.004	0.199
Unemployment (%)	0.864	0.957	0.317	0.068	0.142	0.736
Gross State Product	0.724	0.908	0.622	0.938	0.896	0.950

Note: Because the numbers in the table are *p* values, values less than 0.05 are considered significant.

REFERENCES

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The Review of Economic Studies*, 72(1), 1-19.

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association,* 105(490), 493 – 505.

Abul, N. & Yalcin, T. (2008). Inequality measurement for ordered response health data. *Journal of Health Economics,* 27 (6), 1614-1625.

Allison, R. & Foster, J. (2004). Measuring health inequality using qualitative data. *Journal of Health Economics*, 23 (3), 505-524.

Anderson, M., & Horrigan, J. (2016). Smartphones help those without broadband get online, but don't necessarily bridge the digital divide. Retrieved from http://www.pewresearch.org/fact-tank/2016/10/03/smartphones-help-those-without-broadband-get-online-but-dont-necessarily-bridge-the-digital-divide/.

Anselin, L., Bera AK, Raymond F, Yoon MJ (1996). Simple diagnostic tests for spatial dependence. *Reg Sci Urb Econ* ,26, 77–104

Ashenfelter, O. & Card, D. (1985). Using the Longitudal Structure of Earnings to Estimate the Effect of Training Programs. *The Review of Economics and Statistics*, 67(4), 648-660.

ASR Analytics. (2014). Broadband Technology Opportunities Program Evaluation Study. https://www.ntia.doc.gov/files/ntia/publications/asr_final_report.pdf

Bertrand, M. , Duflo, E. , & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1), 249-275.

Blair, J. & Lacy, M. Statstics of ordinal variation. *Sociological Methods and Research,* 28 (251, 251-280.

Blinder, A. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources, 8*(4), 436-455. doi:10.2307/144855

Cardona M., Schwarz A., Yurtoglu B.B., Zulehner C. (2009). Substitution Between DSL, Cable, and Mobile Broadband Internet Services. In: Curwen P., Haucap J., Preissl B. (eds) Telecommunication Markets. Contributions to Economics. Physica, Heidelberg.

Caliendo, M. and Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys,* 22(1), 31-72.

Census Bureau. (2011,2013,2015). *Computer and Internet Use Supplment*.

Center for Disease Control (CDC). (2011). CDC Health Disparities and Inequalities Report –United States. Vol. 60.

Connected Nation. (2018a). Connected Nation. *Vision and History. R*etreived from https://connectednation.org/vision-and-history/

Connected Nation. (2018b). Connected: Powered by Connected Nation. *Connected Community Engagement Program.* Retrieved from http://connectmycommunity.org/

Connected Nation. (2018c). Connected Nation. *Policy Research.* Retreived from https://connectednation.org/policy-research/

Cotton, J. (1988). On the Decomposition of Wage Differentials. *The Review of Economics and Statistics, 70*(2), 236-243.

Crandall, R., Lehr, W., & Litan, R. (2007). The Effects of Broadband Deployment on Output and Employment: A Cross-sectional Analysis of U.S. Data, *The Brookings Institute,* (Vol. 6).

Crandell, R., Jackson, C., and Singer, H. (2003). The Effect of Ubiquitous Broadband Adoption on Investment, Jobs, and the U.S. Economy. *Criterion Economics, LLC.* Available at http://www.itu.int/net/wsis/stocktaking/docs/activities/1288356543/bbstudyreportcryterion.pdf

Czernich, N., Oliver, F., Kretschmer, T., and Woessmann, L. (2011). Broadband Infrastructure and Economic Growth. *The Economic Journal,* 121(552), 505-532.

Dano, M. (2018). U.S. LTE Buildout timelines. Retrived from https://www.fiercewireless.com/special-report/u-s-lte-buildout-timelines.

Davison, R. & Mckinnon, J.G. (1982). Some Non-nested Hypothesis Tests and Relations Among Them. *The Review of Economic Studies,* XLIX, 551-565.

Davidson, R. & McKinnon, J.G. (1993). Estimation and Inference in Econometrics. *Oxford University Press*, Oxford.

Dinterman, R. and Renkow, M. (2017). Evaluation of USDA's Broadband Loan Program: Impacts on Broadband Provision. *Telecommunications Policy*, 41(2), 140-153.

Donnellan, E. (2017). No Connection: The Issue of Internet on the Reservation. *American Indian Law Journal*, 5,(2), 347-375.

Dufwenberg, M., & Gneezy, U. (1999). Price Competition and Market Concentration: An Experimental Study. *International Journal of Industrial Organization, 18*, 7-22.

EveryoneOn. (2018). Overview of Low Cost Internet Service Offers. Retrieved from https://everyoneon.org/eligibility.

Fairlie, R. (2006). An Extension of the Blinder-Oaxaca Decomposition Technique to Logit and Probit Models. *Advances in Statistical Analysis*, 30(92), 197-206.

Federal Communications Commission. (2011,2015). *Form 477*. Retrieved from: https://www.fcc.gov/general/broadband-deployment-data-fcc-form-477

Federal Communications Commission. (2015). *FCC Finds U.S. Broadband Not Keeping Pace*. Washington, D.C. Retrieved from https://transition.fcc.gov/Daily_Releases/Daily_Business/2015/db0129/DOC-331760A1.pdf.

Federal Commumications Commission. (2015). *Broadband Statsitics Report: Broadband Availability in Urban vs. Rural Areas.* Available online: https://www.broadbandmap.gov/download/Broadband%20Availability%20in%20Rural%20vs%20Urban%20Areas.pdf

Federal Communications Commission. (2017). *Strategies and Recommendations for Promoting Digital Inclusion.* Washington, D.C. Retrieved from https://apps.fcc.gov/edocs_public/attachmatch/DOC-342993A1.pdf

Federal Communications Commission. (2018). *2018 Broadband Deployment Report.* Available online: https://apps.fcc.gov/edocs_public/attachmatch/FCC-18-10A1.pdf

Ferreira, F. & Gignoux, J. (2011). The Measurement of Educational Inequality: Achievement and Opportunity. Institute for the Study of Labor, Discussion Paper No. 6161.

Gallardo, R. (2017). Digital Divide Index. Mississippi State Extension. Extension Report.

Gant, J., Turner-Lee, N., Le, Y., & Miller, J. (2010). National Minority Broadband Adoption: Comparative Trends in Adoption, Acceptance, and Use. *Joint Center for Political and Economics Studies*.

Ghali, M. (2007). Comparison of Two Empirical Cost Functions. *International Journal of Production Economics,* 108, 15-21.

Gimpel, J. G., Lee, F. E., & Thorpe, R. U. (2012). Geographic Distribution of the Federal Stimulus of 2009. *Political Science Quarterly, 127*(4), 567-595. doi:10.1002/j.1538-165X.2012.tb01128.x

Greene, W. (2000). Econometric Analysis, fourth ed. Prentice-Hall, New Jersey.

Hargittai, E. (2002). Second-Level Digital Divide: Differences in People's Online Skills. *First Monday,* 7(4).

Hauge, J. A., & Prieger, J. E. (2010). Demand-side programs to stimulate adoption of broadband, what works? *Review of Network Economics, 9*, 1-38.

Hauge, J. A., & Prieger, J. E. (2015). Evaluating the impact of the American Recovery and Reinvestment Act's BTOP on broadband adoption. *Applied Economics, 47*(60), 6553-6579. doi:10.1080/00036846.2015.1080810

Hill, S., Troshani, I., & Burgan, B. (2014). Broadband Adoption in Regional and Urban Households. *The Journal of Computer Information Systems, 54*(3), 57-66.

Hitt, L., & Tambe, P. (2007). Broadband Adoption and Content Consumption. *Information Economics and Policy,* 19(3-4), 362-378.

Holt,L. & Jamison, M. (2009). Broadband Contributions to Economic Growth: Lessons from the US Experience. *Telecommunications Policy,* 33(10), 575-581.

Horrigan, J. B. (2010). *Broadband Adoption and Use in America*. Retrieved from https://transition.fcc.gov/national-broadband-plan/broadband-adoption-in-america-paper.pdf.

Horrigan, J. B., & Scatterwhite, E. (2010). *Horrigan, John B. and Satterwhite, Ellen, Adoption Paths: The Social Forces that Shape the Uptake of Technology (August 15, 2010). TPRC 2010. Available at SSRN: https://ssrn.com/abstract=1989632*. Paper presented at the TPRC 2010, Arlington, VA. https://ssrn.com/abstract=1989632

Horrigan, J., & Duggan, M. (2015). *Home Broadband 2015*. Retrieved from http://www.pewinternet.org/2015/12/22/2015/Home-Broadband-2015/

Jorda, V., Lopez-Noval, B., & Sarabia, J. (2013). Distributional dynamics of life satisfaction in Europe (1990-2013). *Department of Economics, University of Cantabria Working Papers.*

Johnson, D. & Creech, J. (1983). Ordinal Measures in Multiple Indicator Models: A Simulation Study for Categorization Error. *American Sociological Review*, 48, 398-407.

Jung, G., Kim, Y., Kauffman, R.J. (2014). How can substitution and complementarity effects be leveraged for broadband internet services strategy? 2014 47th Hawaii International Conference on System Sciences (HICSS).

Kandilov, I. & Renkow, M. (2010). Infrastructure Investment and Rural Economic Development: An Evaluation of the USDA's Broadband Loan Program. *Growth and Change*, 41(2), 165-191.

Kaplow, L. (2002). Why Measure Inequality?. NBER Working Paper Series, National Bureau of Economic Research.

Kass, R. & Raftery, A. (1995). Bayes Factors. *Journal of the American Statistical Association*, 90, 773 – 795.

Kastrenakes, J. (2017). FCC Begins Scaling Back Internet Subsidies for Low-Income Consumers. *Policy and Law.* Retrieved from https://www.theverge.com/2017/11/17/16669716/fcc-lifeline-scaled-back-tribal-lands-broadband-discount-limits

Kayvan, M. L., Bahar, M., & Glenn, P. (2014). Broadband Internet adoption challenge: An investigation of broadband utilization in the United States. *Transforming Government: People, Process and Policy, 8*(4), 620-644. doi:doi:10.1108/TG-11-2013-0050

Kim, Y. & Orazem, P. (2017). *Broadband Internet and New Firm Location Decisions in Rural Areas. American Journal of Agricultural Economics*, 99(1), 285-302.

King, H. (2016). U.S. Internet Speeds Just Hit a Milestone. *CNNTech.* Retrieved from http://money.cnn.com/2016/08/04/technology/internet-speed-broadband/index.html

Kobus, M. & Milos, P. (2012). Inequality decomposition by population subgroups for ordinal data. *Journal of health Economics*, 31, 15-21.

Kolko, J. (2012). Broadband and Local Growth. *Journal of Urban Economics*, 71(1), 100-113.

Kongaut, C., & Bohlin, E. (2016). Investigating mobile broadband adoption and usage: A case of smartphones in Sweden. *Telematics and Informatics, 33*(3), 742-752. doi:https://doi.org/10.1016/j.tele.2015.12.002

Koutroumpis, P. (2009). The Economic Impact of Broadband on Growth: A Simultaneous Approach. *Telecommunications Policy*, 33(9), 471-485.

Kruger, L., & Gilroy, A. (2016). *Broadband Internet Access and the Digital Divide: Federal Assistance Programs*. Retrieved from https://fas.org/sgp/crs/misc/RL30719.pdf

Lee, H., Park, N., & Hwang, Y. (2014). A New Dimension of the Digital Divide: Exploring the Relationship Between Brodband Connection, Smartphone Use and Communication Competence. *Telematics and Informatics*, 32, 45-56.

Lee, S., Marcu, M., & Lee, S. (2011). An Emperical Analysis of Fixed and Mobile Broadband Diffusion. *Information Economics and Policy*, 23, 227-233.

Lehr, W., Osorio, C., Gillet, S. & Sirbu, M. (2006). Measuring broadband's economic impact. Paper presented at the Telecommunication Policy Research Conference, Arlington, VA, USA. Available at https://dspace.mit.edu/bitstream/handle/1721.1/102779/esd-wp-2006-02.pdf?sequence=1.

Lifeline. (2017). Lifeline Program for Low-Income Consumers. Retrieved from https://www.fcc.gov/general/lifeline-program-low-income-consumers

Li, H. , Graham, D. , & Majumdar, A. (2012). The effects of congestion charging on road traffic casualties: A causal analysis using difference-in-difference estimation. *Accident Analysis and Prevention*, 49, 366-377.

LaRose, R., Bauer, J. M., DeMaagd, K., Chew, H. E., Ma, W., & Jung, Y. (2014). Public broadband investment priorities in the United States: an analysis of the broadband technology opportunities program. *Government Information Quarterly, 31*(1), 53-64. doi:https://doi.org/10.1016/j.giq.2012.11.004

Makepeace, G., Paci, P., Joshi, H., & Dolton, P. (1999). How Unequally Has Equal Pay Progressed since the 1970s? A Study of Two British Cohorts. *The Journal of Human Resources, 34*(3), 534-556. doi:10.2307/146379

Malamud, O., and Pop-Eleches, C. (2010). Home Computer Use and the Development of Human Capital. *Quarterly Journal of Economics*, 126, 987–1027.

Manlove, J. & Whitacre, B. (2018). Understanding the Trend to Mobile-only Internet Connections: A Decomposition Analysis. *Telecommunications Policy.*

Marmot, M. (2005). Social Determinants of Health Inequalities. *Public Health is a Social Issue*, 365(9464), 1099-1104.

Martyn, F. R. (2013). Global Broadband Benchmarking 2013: Best Practice Lessons for Governments. *Journal of Information Policy, 3*, 619-666. doi:10.5325/jinfopoli.3.2013.0619

Molnar, G., Savage, S., and Sicker, D. (2014). Measuring Broadband Internet Prices. *Journal on Telecomm. & High Tech*, 12, 73-88.

Naga, R. & Stapenhurst, C. (2015). Estimation of Inequality Indices of the Cumulative Distribution Function. *Economic Letters*, 130, 109-112.

National Digital Inclusion Alliance (NDIA). (2018). What We Do. *Retreived from https://www.digitalinclusion.org/corps.*

National Digital Inclusion Alliance (NDIA). (2018). Digital Inclusion Resource Library. Available online: http://library.digitalinclusion.org.

Nielsen, H. (1998). Discrimination and Detailed Decomposition in a Logit Model. *EconomicsLetters*, 61(1), 115-120.

National Telecommunications and Information Administration (NTIA). (1999). *Falling Through the Net: Defining the Digital Divide*. Retrieved from https://www.ntia.doc.gov/legacy/ntiahome/fttn99/FTTN.pdf

National Telecommunications and Information Administration (NTIA). (2013). BTOP Evaluation Study. *Program Reports.* http://www2.ntia.doc.gov/BTOP-Reports#evaluation.

National Telecommunications and Information Administration (NTIA). (2015). Broadband Technology Oppurtunities Program Quarterly Status Report.

National Telecommunications and Information Adminsitration (NTIA). (2002). *A Nation Online: How Americans Are Exoanding their Use of the Internet*. Retrieved from https://www.ntia.doc.gov/legacy/ntiahome/dn/anationonline2.pdf

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, *14*(3), 693-709. doi:10.2307/2525981

Peronard, J.-P., & Just, F. (2011). User motivation for broadband: A rural Danish study. *Telecommunications Policy*, *35*(8), 691-701. doi:https://doi.org/10.1016/j.telpol.2011.06.008

Prieger, J. (2013). The Broadband Digital Divide and the Economic Benefits of Mobile Broadband for Rural Areas. *Telecommunication Policy*, 37(6-7), 483-502.

Prieger, J. (2015). The broadband digital divide and the benefits of mobile broadband for minorities. *The Journal of Economic Inequality, 13*(3), 373-400. doi:10.1007/s10888-015-9296-0

Quaglione, D., Agovino, M., Di Berardino, C., & Sarra, A. (2017). Exploring additional determinants of fixed broadband adoption: policy implications for narrowing the broadband demand gap. *Economics of Innovation and New Technology*, 1-21. doi:10.1080/10438599.2017.1350358

Rappoport P., Taylor L., & Alleman J. (2004). *WTP Analysis of Mobile Internet Demand.* In: Cooper, R., Madden G. (eds) Frontiers of Broadband, Electronic and Mobile Commerce. Contributions to Economics, p. 165-179. https://doi.org/10.1007/978-3-7908-2676-0_11

Reisdorf, B., Hampton, K., Fernandez, L., and Dutton, W. (2018). Broadband to the Neighborhood: Digital Divides in Detroit. Report for Quello Center, Michigan State University. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3103457

Rosston, G., & Wallsten, S. (2013). The Broadband Stimulus: A Rural Boondoggle and Missed Opportunity *Technology Policy Institute*.

Roycroft, T. (2013). Empirical study of broadband adoption using data from the 2009 Residential Energy Consumption Survey. *Journal of Regulatory Economics, 43*(2), 214-228. doi:10.1007/s11149-012-9207-2

Santos, J. & Guerrero, J. (2010). Gini's Concentration Ratio (1908-1914). *Electronic Journal for History of Probability and Statistics,* 6.

Shapley, K., D. Sheehan, C. Maloney, F. Caranikas-Walker, B. Huntsberger, and K. Sturges. "Evaluation of the Texas Technology Immersion Project: Findings from the Second Year." Austin: Texas Center for Educational Research, 2007.

Smith, A. (2015). US Smartphone Use in 2015. Retrieved from http://www.pewinternet.org/2015/04/01/us-smartphone-use-in-2015/

Srinuan, P., Srinuan, C., & Bohlin, E. (2012). Fixed and Mobile Broadband Substitution in Sweden. *Telecommunications Policy*, 36, 237-251.

Stenberg, P., Morehart, M., & Vogel, S., Cromartie, J., Breneman, V., & Brown, D. (2009). Broadband Internet's Value for Rural America. United States Department of Agriculture, Economic Research Service, Economic Research Report.

Sweeney, M. & Rhinesmith, C. (2016). Creating Caring Institutions for Community Informatics. *Information, Communication, and Society*, 20(10), 1482-1497.

Thompson, H. & Garbacz, C. (2008). Broadband Impacts on State GDP : Direct and Indirect Impacts. In 17th Biennial Conference on the International Tele-

Communications Society, Montreal, June 24-27., 1-17. http://www.imaginar.org/taller/its2008/62.pdf

Turner-Lee, N. E., & Grant, J. P. (2010). The Need for Broadband Acceptance: A New Policy Framework for Promoting Digital Inclusion. *Joint Center for Political and Economics Studies*.

United States Census Bureau. (2009). *A Compass for Understanding and Using American Community Survey Data: What Researchers Need to Know*. U.S. Government Printing Office.

United States Census Bureau. (2017). 2017 AMerican Community Survey Research and Evaluation Report Memorandum Series #ACS17-RER-09. U.S. Department of Commerce. Retireved from https://www.census.gov/content/dam/Census/library/working - papers/2017/acs/2017_Lewis_01.pdf

Vigdor, L., Ladd, H., & Martinez, E. (2014). Scaling the Digital Divide: Home Computer Technology and Student Achievement. *Economic Inquiry*, 52(3), 1103-1119.

Warschauer, M. & Dowding, M. (2004). Technology and Social Inclusion: Rethinking the Digital Divide. *Candian Journal of Communication*, 29(1), 108-109.

Wilkinson RG, Pickett K. The Spirit Level: Why Equality is Better for Everyone. London: Penguin, 2010.

Whitacre, B. & Mills, B. (2007). Infrastructure and the Rural - Urban Divide in High-Speed Residential Internet Access. *International Regional Science Review*, 30(3), 249-273.

Whitacre, B., & Rhinesmith, C. (2015). Broadband un-Adopters. *Telecommunications Policy*, *40*, 1-13.

Whitacre, B. (2008). Factors influencing the temporal diffusion of broadband adoption: evidence from Oklahoma. *The Annals of Regional Science*, *42*(3), 661-679. doi:10.1007/s00168-007-0178-7

Whitacre, B. (2010). The Diffusion of Internet Technologies to Rural Communities: A Portrait of Broadband Supply and Demand. *American Behavioral Scientist*, *53*(9), 1283-1303. doi:10.1177/0002764210361684

Whitacre, B., Gallardo, R., & Strover, S. (2014a). Broadband's Contribution to Economic Growth in Rural Areas. *Telecommunications Policy*, *38*(11), 1011-1023. doi:10.1016/j.telpol.2014.05.005

Whitacre, B., Gallardo, R., & Strover, S. (2014b). Does Rural Broadband Impact Jobs and Income? Evidence from Spatial and First-Differenced Regressions. *The Annals of Regional Science*, 53(3), 649-670.

Whitacre, B. & Manlove, J. (2016). Broadband and civic engagement in rural areas: What matters? *Community Development, 47*(5), 700-717. doi:10.1080/15575330.2016.1212910

Whitacre, B. (2017) Internet Options for Low-Income Households in Oklahoma. *Oklahoma State University Extension Publication* AGEC-1065. Retrieved from http://factsheets.okstate.edu/documents/agec-1065-internet-options-for-low-income-households-in-oklahoma/

Wilson, K. (2017). Does Public Competition Crowd Out Private Investment? Evidence from Municipal Provision of Internet Access. NET Institute Working Paper No. 16-16. Retrieved from https://dx.doi.org/10.2139/ssrn.2848569.

Wodajo, T., & Kimmel, J. (2013). Explaining changes in the racial digital divide in the United States from 1997 to 2007. *Economics of Innovation and New Technology, 22*(5), 483-518. doi:10.1080/10438599.2013.776267

Wulf, J., Zelt, S., & Brenner, W. (2013). Fixed and Mobile Broadband Substitution in the OECD Countries -- A Quantitative Analysis of Competitive Effects. Proceedings of the Annual Hawaii International Conference on System Sciences. 1454-1463. 10.1109/HICSS.2013.234.

Xu, Q., Huang, J., Wang, Z., Qian, F., Gerber, A., & Mao, Z. M. (2011). *Cellular data network infrastructure characterization and implication on mobile content placement*. Paper presented at the Proceedings of the ACM SIGMETRICS joint international conference on Measurement and modeling of computer systems, San Jose, California, USA.

Zickuhr, K., & Smith, A. (2012). *Digital Differences*. Retrieved from http://www.pewinternet.org/files/old media/Files/Reports/2012/PIP_Digital_differences_041312.pdf

Zheng, B. (2010). A new approach to measure socioeconomic inequality in health. *Journal of Economic Inequality*, 16, 177-188.

Zheng, B. (2008). Measuring inequality with ordinal data: a note. *Research on Economic Inequality*, 555-577.

Zumbo, B. & Zimmerman, D. (1993). Is the Selection of Statistical Methods Governed by Level of Measurement? *Candian Psychology*, 34, 390-400.

APPENDICES

Appendix 1A. Mobile-only Adoption Rates
By Socio-economic Characteristics

Characteristic	2011	2015
Mobile-Only Adopters	8.73%	19.96%
Income		
Less than $10,000	10.05%	21.62%
$10,000 - $19,999	7.51%	19.96%
$20,000 - $29,999	9.49%	21.44%
$30,000 - $39,999	9.09%	22.09%
$40,000 - $49,999	9.40%	20.82%
$50,000 - $59,999	8.78%	20.65%
$60,000 - $74,999	8.93%	19.95%
$75,000 - $99,999	8.80%	19.05%
$100,000 - $149,999	7.79%	17.71%
More than $150,000	7.71%	16.09%
Education		
High School	8.21%	20.51%
Some College	10.68%	20.54%
Bachelor	8.34%	18.17%
Graduate Degree	9.18%	16.53%
Race		
Black	11.11%	24.27%
Asian	6.45%	17.17%
Hispanic	9.81%	25.33%
Non-Metro Status	9.13%	22.30%
Age		
Less than 35	13.17%	24.22%
35 to 54	8.93%	22.09%
55 or More	4.33%	14.90%
Retired	3.53%	12.44%
Employed	10.40%	22.50%
Unemployed	12.07%	25.14%

Appendix 2A. Effects of Connected Nation on Broadband Adoption, with Covariates (State-Fixed Effects)

	1		2		3		4		5	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Program effect	-0.010	0.043	-0.077	0.048	-0.020	0.023	-0.166	0.021***	-0.109	0.032***
Yearly Program Effect	-	-	-	-	-	-	0.047	0.025*	0.047	0.019**
Log of Population	-	-	-	-	0.188	0.015***	-	-	0.188	0.015***
Log of Per Capita Income	-	-	-	-	0.739	0.075***	-	-	0.739	0.075***
Poverty	-	-	-	-	-0.030	0.003***	-	-	-0.030	0.003***
Unemployment	-	-	-	-	-0.030	0.005***	-	-	-0.030	0.005***
2009	0.095	0.023***	0.095	0.014***	0.236	0.021***	0.095	0.014***	0.236	0.021***
2010	0.297	0.023***	0.297	0.029***	0.442	0.030***	0.297	0.029***	0.442	0.030***
2011	0.513	0.023***	0.513	0.028***	0.602	0.025***	0.513	0.028***	0.602	0.025***
2012	0.577	0.023***	0.579	0.027***	0.614	0.026***	0.581	0.027***	0.616	0.026***
2013	0.732	0.023***	0.734	0.028***	0.739	0.025***	0.735	0.028***	0.740	0.025***
2014	0.887	0.023***	0.889	0.035***	0.826	0.033***	0.890	0.035***	0.826	0.033***
2015	0.988	0.023***	0.990	0.036***	0.874	0.034***	0.989	0.036***	0.873	0.034***
2016	0.863	0.023***	0.865	0.066***	0.747	0.056***	0.862	0.066***	0.745	0.056***
Constant	2.771	0.016***	2.771	0.023***	-6.217	0.859***	2.771	0.023***	-6.214	0.859***
State Fixed Effects	No		Yes		Yes		No		Yes	
Adjusted R^2	0.124		0.276		0.484		0.276		0.484	

Note: For model 2-5 standard errors are calculated using a Huber-White robust variance matrix that allows for clustering at the state-level.; *, **, *** represent statistical significance at the p=0.10, 0.05, and 0.01 levels, respectively.

Appendix 2B. Effects of Connected Nation on Broadband Adoption, with Covariates (County-Fixed Effects)

	1		2		3		4		5	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Program effect	-0.010	0.043	0.044	0.037	0.033	0.036	-0.034	0.039	-0.043	0.039
Yearly Program Effect	-	-	-	-	-	-	0.041	0.017**	0.040	0.017**
Log of Population	-	-	-	-	0.340	0.239	-	-	0.345	0.239
Log of Per Capita Income	-	-	-	-	0.464	0.090***	-	-	0.464	0.090***
Poverty	-	-	-	-	-0.010	0.002**	-	-	-0.010	0.002**
Unemployment	-	-	-	-	-0.026	0.004***	-	-	-0.026	0.004***
2009	0.095	0.023***	0.095	0.008***	0.194	0.017***	0.095	0.008***	0.195	0.017***
2010	0.297	0.023***	0.297	0.012***	0.399	0.020***	0.297	0.012***	0.399	0.020***
2011	0.513	0.023***	0.513	0.012***	0.571	0.020***	0.513	0.012***	0.571	0.020***
2012	0.577	0.023***	0.576	0.012***	0.594	0.020***	0.578	0.012***	0.596	0.020***
2013	0.732	0.023***	0.730	0.012***	0.726	0.020***	0.731	0.012***	0.728	0.020***
2014	0.887	0.023***	0.886	0.013***	0.834	0.021***	0.886	0.013***	0.834	0.021***
2015	0.988	0.023***	0.986	0.013***	0.902	0.021***	0.985	0.013***	0.901	0.021***
2016	0.863	0.023***	0.861	0.025***	0.785	0.030***	0.859	0.025***	0.783	0.031***
Constant	2.771	0.016***	2.771	0.008***	-5.237	2.690	2.771	0.008***	-5.280	2.689
County Fixed Effects	No		Yes		Yes		No		Yes	
Adjusted R^2	0.124		0.645		0.653		0.645		0.653	

Note: For model 2-5 standard errors are calculated using a Huber-White robust variance matrix that allows for clustering at the county-level; *, **, *** represent statistical significance at the p=0.10, 0.05, and 0.01 levels, respectively.

Appendix 3A. State Level Absolute Value Index

	2011				2013				2015			
	$I_{2,1}$	$I_{3,1}$	$I_{4,1}$	% Adoption	$I_{2,1}$	$I_{3,1}$	$I_{4,1}$	% Adoption	$I_{2,1}$	$I_{3,1}$	$I_{4,1}$	% Adoption
AK	1.43	1.83	2.18	73.1%	1.37	1.77	2.1	80.4%	1.43	1.84	2.19	83.7%
AL	1.69	2.1	2.46	59.0%	1.69	2.11	2.47	61.3%	1.73	2.15	2.52	68.3%
AR	1.68	2.1	2.46	62.7%	1.71	2.13	2.51	64.9%	1.72	2.14	2.51	70.5%
AZ	1.46	1.86	2.21	71.2%	1.53	1.94	2.3	70.6%	1.59	2.01	2.38	72.1%
CA	1.45	1.85	2.19	73.3%	1.4	1.8	2.15	78.6%	1.52	1.93	2.3	77.3%
CO	1.4	1.8	2.15	78.7%	1.31	1.71	2.04	83.9%	1.57	1.98	2.35	76.2%
CT	1.35	1.73	2.06	76.1%	1.32	1.71	2.04	80.3%	1.47	1.88	2.24	78.2%
DE	1.49	1.9	2.24	70.9%	1.38	1.78	2.12	76.0%	1.51	1.92	2.28	77.7%
FL	1.4	1.8	2.13	74.4%	1.4	1.8	2.14	75.3%	1.57	1.98	2.34	72.4%
GA	1.53	1.93	2.28	68.2%	1.52	1.93	2.29	73.2%	1.55	1.96	2.33	77.3%
HI	1.53	1.93	2.28	69.9%	1.52	1.93	2.29	78.4%	1.52	1.93	2.29	74.1%
IA	1.53	1.94	2.29	68.6%	1.49	1.89	2.25	75.3%	1.52	1.93	2.29	76.4%
ID	1.52	1.93	2.28	70.8%	1.5	1.91	2.27	76.5%	1.52	1.93	2.29	81.9%
IL	1.47	1.88	2.23	72.3%	1.41	1.82	2.16	77.3%	1.49	1.89	2.25	79.9%
IN	1.61	2.03	2.38	62.7%	1.55	1.96	2.32	69.9%	1.57	1.98	2.34	74.3%
KS	1.44	1.84	2.19	73.9%	1.49	1.9	2.26	76.3%	1.56	1.97	2.34	76.0%
KY	1.62	2.03	2.38	62.0%	1.51	1.92	2.27	70.2%	1.54	1.95	2.32	73.8%
LA	1.62	2.03	2.39	64.7%	1.56	1.97	2.33	68.5%	1.67	2.09	2.47	71.9%
MA	1.39	1.79	2.13	75.8%	1.27	1.65	1.98	82.4%	1.54	1.96	2.32	75.5%
MD	1.47	1.88	2.23	77.5%	1.34	1.73	2.07	79.1%	1.42	1.82	2.17	80.7%
ME	1.44	1.84	2.18	71.6%	1.41	1.81	2.15	75.1%	1.45	1.86	2.21	77.4%
MI	1.54	1.95	2.3	67.7%	1.47	1.88	2.23	74.5%	1.54	1.95	2.31	73.6%
MN	1.43	1.83	2.17	74.7%	1.34	1.74	2.08	82.4%	1.43	1.83	2.19	82.2%
MO	1.59	2.01	2.36	65.7%	1.51	1.91	2.27	72.5%	1.66	2.08	2.45	73.5%
MS	1.79	2.22	2.58	55.2%	1.62	2.03	2.4	68.8%	1.81	2.23	2.61	67.4%
MT	1.65	2.06	2.42	63.4%	1.51	1.91	2.26	70.4%	1.55	1.96	2.32	73.2%
NC	1.51	1.92	2.26	67.7%	1.5	1.91	2.26	71.4%	1.61	2.02	2.39	70.2%
ND	1.5	1.91	2.26	71.6%	1.41	1.81	2.16	81.6%	1.57	1.99	2.35	73.6%
NE	1.52	1.92	2.28	69.3%	1.46	1.86	2.21	75.2%	1.52	1.94	2.3	77.3%
NH	1.35	1.74	2.08	77.9%	1.27	1.66	1.98	83.5%	1.45	1.86	2.21	81.6%
NJ	1.4	1.79	2.13	75.9%	1.31	1.7	2.02	79.7%	1.46	1.87	2.23	78.9%
NM	1.72	2.15	2.5	57.5%	1.6	2.01	2.37	66.9%	1.69	2.11	2.48	70.7%
NV	1.43	1.84	2.19	76.8%	1.57	1.98	2.35	76.3%	1.48	1.88	2.24	81.3%
NY	1.45	1.85	2.19	71.7%	1.39	1.78	2.12	75.3%	1.55	1.96	2.32	73.7%
OH	1.55	1.95	2.3	65.9%	1.5	1.91	2.27	74.2%	1.57	1.98	2.34	73.0%
OK	1.65	2.06	2.42	65.9%	1.65	2.06	2.43	74.2%	1.63	2.05	2.42	73.0%
OR	1.51	1.92	2.27	75.7%	1.38	1.78	2.12	79.8%	1.38	1.78	2.13	80.2%
PA	1.51	1.92	2.26	68.4%	1.45	1.86	2.21	73.8%	1.49	1.89	2.24	72.4%
RI	1.48	1.89	2.24	71.8%	1.39	1.78	2.12	77.2%	1.45	1.85	2.21	79.8%
SC	1.63	2.05	2.4	63.2%	1.64	2.05	2.41	64.6%	1.56	1.98	2.34	74.1%
SD	1.57	1.98	2.33	67.9%	1.5	1.9	2.26	74.1%	1.56	1.98	2.34	72.2%
TN	1.64	2.06	2.41	63.0%	1.6	2.02	2.37	65.9%	1.63	2.04	2.41	67.7%
TX	1.61	2.03	2.39	67.0%	1.53	1.94	2.3	75.4%	1.66	2.08	2.45	74.6%
UT	1.41	1.81	2.15	77.1%	1.35	1.75	2.09	84.4%	1.44	1.84	2.19	82.2%
VA	1.57	1.98	2.34	69.6%	1.41	1.81	2.16	78.8%	1.45	1.86	2.21	77.4%
VT	1.47	1.87	2.21	67.9%	1.38	1.77	2.11	77.2%	1.45	1.85	2.21	81.8%
WA	1.38	1.78	2.12	78.7%	1.33	1.73	2.07	82.3%	1.45	1.85	2.21	81.0%
WI	1.46	1.85	2.2	70.7%	1.49	1.9	2.25	71.6%	1.38	1.78	2.13	81.9%
WV	1.65	2.06	2.41	58.4%	1.53	1.93	2.27	66.2%	1.6	2.01	2.37	69.3%
WY	1.61	2.02	2.38	67.7%	1.45	1.85	2.2	77.5%	1.6	2.01	2.37	69.3%

VITA

Jacob Lee Manlove

Candidate for the Degree of

Doctor of Philosophy

Thesis: THREE ESSAYS ON BROADBAND ADOPTION

Major Field: Agricultural Economics

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Agricultural Economics at Oklahoma State University, Stillwater, Oklahoma in May, 2018.

Completed the requirements for the Master of Science in Agricultural Economics at University of Arkansas, Fayetteville, Arkansas in 2015.

Completed the requirements for the Bachelor of Arts in Economics at University of Arkansas, Fayetteville, Arkansas in 2013.

Experience:

Oklahoma State University, Department of Agricultural Economics

Graduate Research Assistant	2015 - 2018
Instructor, Quantitative Methods for Agriculture Economics	2017

Bunge North America, St. Louis, MO

Planning Analyst	2014 – 2015